INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

DEPARTMENT OF INFORMATION TECHNOLOGY

INVESTIGATE A CNN PRE-TRAINED MODEL FOR CLASSIFYING THE STAGES OF TOOTH CAVITY DISEASE.

By

Adamu Yadeta

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF JIMMA UNIVERSITY IN PARTIAL FULFILLMENT FOR THE DEGREE OF MASTER OF SCIENCE IN INFORMATION TECHNOLOGY

DECEMBER 2023

JIMMA, OROMIA, ETHIOPIA

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

GRADUATED PROGRAM IN INFORMATION TECHNOLOGY

INVESTIGATE A CNN PRE-TRAINED MODEL FOR CLASSIFYING THE STAGES OF TOOTH CAVITY DISEASE.

By: Adamu Yadeta

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF JIMMA UNIVERSITY IN PARTIAL FULFILLMENT FOR THE DEGREE OF MASTER OF SCIENCE IN INFORMATION TECHNOLOGY

Advisor: Dr. Teklu Urgessa (Associate Professor)

Co-advisor: Mr. Alemisa Endebu (MSC)

DECEMBER 2023

JIMMA, OROMIA, ETHIOPIA

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

GRADUATED PROGRAM IN INFORMATION TECHNOLOGY

This is to certify that the thesis prepared by Adamu Yadeta Amena, entitled "**Investigate a CNN Pre-Trained Model for Classifying the Stages of Tooth Cavity Disease**" Submitted in partial fulfilment of the requirements for the Degree of Masters of Science in Information Technology compiled with the regularizations of the University and meets the accepted standards concerning originality and quality.

By Adamu Yadeta Amena

Approval Signature of the board of Examiners.

Name	**Signature**	**Date**
Dr. Teklu Urgessa (Associate Professor) (**Principal visor**)		___________
Mr. Alemisa Endebu (MSC) **(Co-advisor)**	____________	___________
Mr. Worku Birhanie (MSC) (**Internal Examiner**)	_____________	____________
Mr.Yonas (**Chair Person**)	____________	___________
Dr. Tibebe Beshah (Associate professor) (**External Examiner**)		__________

DECLARATION

I confirm that the research titled "**Investigate a CNN Pre-Trained Model for Classifying the Stages of Tooth Cavity Disease**" conducted within the **information technology department**, is entirely my own work. All external sources referenced in this study have been duly acknowledged and included in the bibliography. Additionally, I affirm that this thesis has not been previously submitted to any other educational institution for credit towards any academic degree.

Adamu Yadeta Amena	__________________	____________________
Name	**Sign**	**Date**

ACKNOWLEDGMENT

First, I like to thank and praise the Almighty God for showering His blessings upon me throughout my research journey, enabling me to complete my work. I am immensely grateful to my esteemed research advisors, **Dr. Teklu Urgessa** (Associate Professor) and **Mr. Alemisa Endebu**, who graciously granted me the opportunity to conduct this research and provided invaluable guidance every step of the way. Their unwavering dedication, sincerity, and unwavering encouragement have served as a profound source of inspiration, pushing me to exert my utmost efforts. They furnished me with the systematic approach necessary to undertake the research and present the findings with utmost clarity.

In addition to my advisors, I extend my deep and sincere appreciation to **Dr. Bereket**, a distinguished OMF Surgeon, and the other specialist doctors in the dentistry department at Jimma University Specialized Referral Hospital. Furthermore, I am grateful to **Dr. Chala Hailu**, the proprietor of Waliin Dental Clinic in Jimma town and an expert in orthodontic surgery, for their unwavering supervision throughout the process of dataset preparation, document analysis, data labeling, and invaluable insights, which persisted until my work reached completion.

I cannot overlook the immeasurable support and guidance from my beloved family. Your constant encouragement and guidance in pursuing my aspirations have been truly remarkable. I am deeply appreciative of my family conscientious presence in my life. I hold each one of you in great admiration. Lastly, I extend my heartfelt gratitude to all those who helped during my research, even if their names have not been mentioned. Your contributions have not gone unnoticed and have played a significant role in the successful culmination of my work.

Abstract:

Objectives: Dental cavity diseases are very common diseases and half of the world population suffers from it. Dental caries has been a common health issue throughout the world, which can even lead to dental pulp and root apical inflammation eventually and the most frequent dental health issue in the general population. Therefore, timely and effective treatment of dental caries is vital for patients to reduce pain. To this end, Deep learning techniques have demonstrated remarkable diagnostic capabilities within the radiology field. The aim of this study is investigate a CNN pre-trained model for classifying the stages of tooth cavity diseases and additionally, we sought to compare the classification results achieved by deep learning models with those of expert dentists.

Methods: In this study, two dental experts participated in preparing and evaluating collected 4725 dental X-ray images. The combination of these images formed our reference dataset. From this dataset, we established training and validation set consisting of 4269 images, as well as a separate test set comprising 456 images. To achieve our objectives, we employed a convolutional neural network and utilized two pre-trained models, VGG16 and InceptionResNetV2. All These models were developed to detect the stages of the cavity and classify them according to their labels: Enamel, Dentin, Pulp, and Healthy tooth.

Results: Based on trained models, the **CNN** model has achieved a Base accuracy of **0.899%** and a validation rate of **0.910%**, **VGG16** scored an accuracy of **0.9243%** and a validation rate of **0.9557%**, while InceptionResNetV2 scored an accuracy of **0.977%** and a validation of **0.978%**. The expert and the neural network demonstrated comparable results across the metrics (F1 score, precision, and recall). In terms of cavity stage classification, **InceptionResNetV2** exhibited an impressive best accuracy of **97.7%** than the other two models. Furthermore, the recall results for InceptionResNetV2 in the **ED/DD/PD/HT** stages were **0.96%, 1.00%, 0.94%, and 1.00%**, respectively.

Conclusions: This paper concludes that the deep learning methods we implemented are comparable performance to experts in determining tooth cavity stages using dental panoramic radiographs. The application of these techniques could have significant implications in dental diagnostics to determine the stages of cavities in the right way.

Table Contents

LIST OF FIGURES

LIST OF TABLES

ACRONYMS AND ABBREVIATIONS

CNN	Convolutional Neural Network
ANN	Artificial Neural Network
DNN	Deep Neural Network
WHO	World Health Organization
MD	Medical Diagnosis
DC	Dental Cavity
HC	Health care
AI	Artificial Intelligence
VGG	Visual Geometry Group
LR	Learning Rate
RNN	Recurrent Neural network
DBN	Deep Belief Network
DD	Dentin Decay
ED	Enamel Decay
PD	Pulp Decay
DM	Demineralization
OPT	Optimization
KS	Kernel Size
ResNet	Residual Neural Networks
DenseNet	Densely Connected Convolutional Networks
RNN	Re-current Neural Networks

CHAPTER ONE

INTRODUCTION

1.1 Backgrounds

Medical diagnosis (MD) involves analyzing symptoms and signs to identify diseases, playing a vital role in disease management and prevention. Regardless of whether the impact is on an individual or an entire society, disease control is paramount. Consequently, prompt detection and diagnosis are crucial in halting the further spread of any disease outbreak. Tooth cavities (1) represent a significant global public health issue. The majority of oral health problems are preventable if they are identified and treated promptly. These include tooth cavities, oral cancers, oro-dental trauma, and noma, which start in the mouth. "The Global Disease Study report from 2019 estimates that this diseases affected about 3.5 billion people globally, with cavity of long time illness tooth with accounting for 520 million of these cases; additionally, this estimate indicates that 530 million children under the age of five have dental cavities in their teeth" (2).

In general, dental cavities, also called caries or decays, are a prevalent ailment impacting individuals globally. The condition arises from oral bacteria generated by lactic acids present in the everyday food and drinks we consume. These bacteria influence the natural minerals within our tooth structures. Without proper treatment, these bacteria can lead to discomfort, infection, and potential tooth loss by exposing and demineralizing the layers of our teeth, creating a small gap between them (3). A cavity or hole created by the chipped enamel eventually becomes visible in the tooth. If left untreated, this cavity or hole can cause pain, sensitivity, and more decay and infection. A dental cavity can develop in multiple phases. How much tooth decay and damage there is can be used to identify these stages (3).

Currently, detecting and determining the stages of tooth cavities is diagnosed by visual evaluation. This ocular inspection to detect and classify the dental cavity is the most challenging in the department of dentistry. In the medical diagnosis process, visual evaluation and oral questions about the disease's symptoms and signs are the first steps in diagnosis. The other method to identify and detect diseases is a radiographic examination which is often used as one method in the main diagnosis. Dental disease can present with a wide range of symptoms, many of which may not be visible to the naked eye. For example, early-stage tooth decay or gum disease may not be easily detected visually, requiring additional diagnostic tools such as X-rays and diagnostic tests. The interpretation of visual findings is subjective and can vary between different dental professionals. This subjectivity can affect diagnostic accuracy and treatment decisions (4).

To solve the problem, we developed an intelligent deep-learning convolutional neural network pre-trained model for detecting and determining the stages of this tooth cavity. Deep learning methods in particular, convolutional neural networks or CNNs are being used by many different businesses these days to process medical images (5). Deep learning is a major field of machine learning research. It uses the hierarchical characteristics synthetic neural network and biological brain systems to its fullest, processing data and gaining high-level features by adopting and learning low-level ones (6). Periodontal diseases and orthodontics are two areas of dentistry where CNNs have been applied. A small number of studies have focused on caries, although they have mainly used near-infrared Trans-illumination and radiography pictures as the basis for their deep learning models, rather than camera-based images. In general, this network simply provided for image recognition, classification, and a specific class of neural networks intended to extract unique properties from picture data. Convolutional neural networks, or CNNs for short, are a type of neural network designed to handle data with input shapes similar to 2D matrices, like pictures (7).

This paper concentrated on the uniform design of low-level features, such as shape, size, and color, in order to increase the accuracy of image classification. Using a multilayer network model, deep learning enables the training of large-scale datasets. This paper also chose to apply a deep learning technique that could identify the cavity's location instantly by utilizing four different components. There is a lack of insufficient image data in different dentistry departments and require more time and resources (8). These four stages of tooth cavity images are collected from different dentistry clinics, hospitals, and other secondary sources. Lastly, we assessed how well the trained algorithms performed by predicting real photos—which are often captured by X-ray images at dental clinics—using unseen image datasets that are not included in the training dataset. Additionally, in this work employed several pre-process algorithms, feature selection strategies, CNN algorithm assessment metrics, and varied parameters to enhance the performance of certain trained algorithms.

1.2 Overview of Dental Cavity Disease

Cavities are areas on the hard surfaces of our teeth which grow into small gaps/hole or apertures due to persistent damage. Cavities, sometimes referred to as caries or tooth decay, are the result of numerous circumstances, including oral bacteria, frequent snacking, consumption of sugary drinks, and insufficient brushing of teeth (9). If not addressed, cavities may result in pain and infections and make it challenging to eat, play, speak, and concentrate in class. Without treatment, cavities may develop into an abscess under the gum line, which would be quite dangerous.

Caries may develop on any part of the tooth However; they are most frequently observed on smooth surfaces such as Enamel is gradually dissolved by this filling in of the depression. With proper oral hygiene, we can sometimes even reverse it. In between teeth, this type of dental illness usually affects people in their 20s. Deterioration of pits and fissures: Tooth decay forms on the upper surface of your teeth, the area you chew on. It is plausible that the anterior surfaces of your rear teeth could also be impacted by decay. A common occurrence throughout adolescence is the rapid progression of pit and fissure degradation. Root decay: In adults, receding gums raise the chance of developing root decay (10).

After a cavity happens, different symptoms occur in daily life such as Holes or pits in our teeth, A toothache or other pain that strikes without warning, delicate teeth, Anguish when we consume sweet, hot, or cold foods or beverages, Teeth stains that are brown, black, or white and ache as we bite into it. If left untreated, cavities can develop into discomfort and infections, which can interfere with speaking, eating, playing, and learning. If cavities are left untreated, they may develop into an abscess (major diseases) beneath the gums. This infection can travel to other areas of our physique and cause catastrophic, occasionally fatal consequences (11). There isn't as much information available on oral health in Africa because it receives less attention there. On the other hand, non-communicable diseases—which include oral disorders—are on the rise, and there are significant differences in dental health between high- and low-income countries on the continent, including Ethiopia. There are reports that the prevalence of dental cavities varies across Africa; in Nigeria, it is between 12.6% and 24.1%, in Kenya, it is 43.3%, and in Sudan, it is 30.5% (12). According to (13) in Gondar Town (36.3%), Addis Ababa (47.3%), and Bahir Dar (21.8%), dental caries was found, according to an Ethiopian study, and 48.5% in Finote Selam.

The socioeconomic and demographic characteristics of Ethiopians have not, as far as we are aware, been thoroughly investigated as dental caries risk factors (14). Yet as the results of earlier research demonstrate, oral health problem prevention and treatment have received little attention from the public or private sectors, and the dental care that is now available is costly and associated with more significant global diseases (15). However, as evidenced by earlier research, oral health conditions have received little attention from either the public or private sectors, and the dental care that is now available is costly and associated with more major global health issues. Every one of the aforementioned studies indicates that there are multiple risk factors associated with the potential development of dental decay. Although we cannot control the majority of risk factors, we can prevent them from occurring by brushing our teeth as soon as we consume sugar. Maintaining proper dental hygiene and physical health depends on limiting these hazards, especially by making wise behavioral decisions. The phases at which cavities form on teeth are typically used to diagnose and treat tooth cavity diseases.

1.3 Motivation

Motivation in AI and robotics refers to the mechanisms that artificial agents, like robots, might use to exhibit inherently rewarding activities like curiosity and exploration. Dental caries pose a severe threat to overall health. There is a gap in knowledge regarding the prevalence and underlying causes of disorders associated with dental care and oral health in Ethiopia, and there has been less focus on the prevention and management of oral health conditions. We were able to understand the benefits of deep learning models and how they may be used to solve practical problems in healthcare facilities after reading several papers.

After doing the initial survey and reviewing pertinent papers, we determined which research gaps needed to be filled. In addition, several researchers have developed deep neural network models that support healthcare, individual health status, and classification and segmentation (20). We examined the viability of applying deep learning models from those articles and found that they had additional benefits for the healthcare industry, particularly for the classification of photos created by Yushi Chen, Member, IEEE (21).

1.4 Statements of the Problems

Cavity is the main prevalent dental issue worldwide and can affect individuals of any age (8). Most people only picture microscopic holes on dental surfaces when they think of cavities. This description is true, yet you might have pain that makes it difficult for you to go about your everyday life. Since it is typically not potentially fatal, the largest issue is that many people see clinics for treatment when their caries have progressed to advanced stages of caries that are challenging to treat. Since cavities can manifest in a variety of ways, one of the current challenges facing dentists is identifying the stages of the disease (16). The traditional method of cavity diagnosis makes use of a dental probe and primarily relies on unassisted visual inspection (17) and the paper attempt to train deep convolutional neural networks (CNNs) to detect caries lesions on Near-Infrared Light Trans illumination (NILT) imagery obtained either in vitro or in vivo and to assess the models' generalizability. Methods: In vitro, 226 extracted posterior permanent human teeth were mounted in a diagnostic model in a dummy head. Then, NILT images were generated (DIAGNOcam, KaVo, Biberach), and images were segmented tooth-wise. Generally, it's important to note that, the following points are some problem addresses in this department to determine the stages of caries efficiently according to their classes based on their extent.

Subjectivity in diagnosis: Assessing the stage of tooth cavity progression may involve some degrees of subjectivity, especially in the early stages. Based on the experience and academic rank they have Different dental professionals may interpret the same cavity differently.

Lack of Standardization: There might be variations in the criteria used by different dental practitioners to define and classify the stages of tooth decay.

Early Detection Challenges: Detecting cavities in their early stages can be challenging, as some lesions may be microscopic or hidden in hard-to-reach areas (18) . Early detection is crucial for conservative treatment and preventing further decay.

Resource Constraints: In some healthcare settings, especially in underserved areas or countries with limited resources, access to advanced diagnostic tools and technologies for accurate cavity assessment may be restricted. Treating without identifying at which stage is, leads to making wrong decisions (19).

1.5 Research Questions

- ✓ **RQ1**: How effective are deep learning techniques, specifically a pre-trained Convolutional neural network (CNN), in the accurate predictions of tooth cavity stages using dental X-ray images?
- ✓ **RQ2**: What is the performance comparison between the implemented CNN model and expert dentists in determining different stages of tooth cavity diseases?
- ✓ **RQ3**: To what extent do pre-trained models; contribute to the improvement of classification accuracy for tooth cavity diseases compared to a non-pre-trained model?

1.6 Objectives of the study

1.6.1 The General Objective

The main goal of this study is investigate robust deep learning approaches, specially a pre-trained convolutional neural network (CNN) model, for the accurate and efficient determining of tooth cavity stages based on radiographic extensions in dental x-ray images.

1.6.2 Specific Objectives

We determine the following specific tasks to accomplish the overall goal.

- ✓ To data collection and preparation on the entire dental cavity X-ray image datasets.
- ✓ To conduct a literature review to identify the related work, gaps, methods and limitation for tooth cavity stage classification.
- ✓ To implement preprocessing techniques such as resizing, normalization, and noise reduction to enhance the quality and variability of the dataset to improve the model's generalization.
- ✓ To choose optimal deep learning model architecture for dental caries classification and adapt or design model architecture that accommodates the characteristics of dental images.
- ✓ To train the selected deep learning model to accurately classify dental caries in images and experiment with hyper parameter tuning and regularization techniques to optimize model performance.

- ✓ To define and use appropriate metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve to evaluate the performance of the trained model and also validate the model's performance on a separate test set and compare the performance of the deep learning model with existing baselines or state-of-the-art methods and lastly conduct a comparative analysis to highlight the strengths and limitations of the proposed deep learning approach.

1.7 Significance

The main importance of this work is the simple use of artificial intelligence (AI) algorithms to identify the various phases of dental cavity disease. When caries affects pulp, dentin, and enamel, it can be very painful and challenging to stop in its early stages. This can happen when the dental cavity stage is incorrectly identified (22). As a result, automatically detecting dental cavities using the studied deep learning models could lead to a treatment plan based on science. The benefits of this recently developed technology for precisely determining the stages of a tooth cavity and the system's beneficiary are as follows.

- ✓ **Dentistry department:** Tailored treatment plans different treatment modalities are needed depending on the stage of dental caries. For instance, a minor cavity might just need a filling, whereas a more advanced cavity might need more involved care, including crown placement or root canal therapy. Dentists can optimize oral health outcomes by developing customized treatment plans that cater to each patient's unique needs by precisely identifying the stage of a cavity. **Early detection and intervention**: Identifying a cavity in its early stages allows for prompt treatment, which can help prevent the progression of decay.
- ✓ **Patients:** patients can get **cost-effective management treatments**. Compared to advanced cavities, early-stage cavities can frequently be treated with less invasive and costly methods. By detecting and treating cavities promptly, patients can potentially avoid the need for more costly and complex interventions, such as root canals or dental implants. **Prevention of tooth loss** Left untreated, a cavity can expand and affect deeper layers of the tooth, potentially leading to infections, abscesses, or even tooth loss.

- ✓ **Researcher:** From this study, the researchers can get some ideas, methods, gaps, and techniques to detect and classify medical images according to their labels. And also they provide the gaps of this study by investigating the best solution for the purpose.

1.8 Scope of the study

The scope of this research starts from identifying the area of the study to implementing and evaluating the model on specified problem descriptions of dental cavity stages by combining several AI-based technologies. Here are some key areas where this study focused on it, from the start to the results.

- ✓ Collecting and preparing all the dental cavity X-ray image datasets for training and testing the model and selecting the best data preprocessing algorithms to increase our model performance and for feature extraction tasks.
- ✓ Investigate the robust model architecture and apply different hyper-parameters for determining the stages of tooth cavities based on labelled datasets by experts in a field.
- ✓ Evaluating and comparing the implemented model performance with different evaluation metrics and selecting the high-accuracy model from each, based on which model achieves a remarkable accuracy based on both training and testing datasets.
- ✓ Finally, we find out the system performance and gaps by comparing them with previous related papers and put the feature directions on the limitation part of the paper.

1.9 Limitations of the study

The classification of dental caries has been the subject of several artificial intelligence articles. It is significant to remember that these stages of tooth cavity are distinct from the caries classifications that have been the focus of earlier studies. After looking through several related papers on the topic, we found that the tooth caries classification is also grouped into classes I, II, III, IV, and V (23). The depth of the cavity in our teeth determines the stages of the cavity formed on which layer of our tooth caries formed. During the implementation of this study, different challenges and limitations were encountered from the start to the end of the result such as:

- ✓ **Data imbalance:** The availability of diverse and well-balanced datasets for all the stages of tooth cavity disease may be limited, potentially leading to challenges in model generalization, particularly for less prevalent stages. Because of this unavailability of all cavity stages, this paper only focused on three stages of the cavity that means, enamel, dentin, and pulp decay, which means the two (demineralization and Abscesses) are not concluded in this paper.

- ✓ **Human variability:** Interpreting dental X-ray images can be subjective, and there may be variability among expert dentists in determining certain stages of tooth cavity diseases. This introduces a degree of subjectivity in the comparison with the model's predictions. Especially during dataset collection and preparation, it is a challenge (18).
- ✓ **Resource requirement:** Implementing and fine-tuning deep learning models, especially pre-trained architectures may require significant computational resources, limiting the accessibility of the proposed framework in resource-constrained environments. Therefore, to perform models with high accuracy by adding the value of optimizer and hype-parameters the resource we use for this study also does not generally meet these requirements.
- ✓ **Influence of image quality:** The model performance may be sensitive to variations in image quality, including factors such as resolution, noise and artefacts, which could affect the accuracy of cavity stage classification.

1.10 Organizations of the Study

Here, we make an effort to clarify each chapter's topics in our study report. The first chapter includes information about the study's history, purpose, problem description, research questions, constraints, scope, and importance. Chapter 2 covers reviews of the literature and associated works. The third chapter covers the study plan and resources used to create the recommended system. These chapters discuss several techniques related to gathering data, preparing and preprocessing datasets, extracting features from datasets, choosing models, and more.

The suggested system model architecture, the implementation flow chart, and the model implementation are all included in Chapter 4. A discussion of how the proposed system addresses the research question and how it varies from earlier work on classifying medical images is included in Chapter 5, which also includes the results of the proposed system development and the evaluation results from the proposed model, based on our dataset and human review. Three main topics were covered in the final chapter: recommendations based on the research, future work, and the general role conclusions done in this study.

CHAPTER 2

Literature Reviews

2.1 Introduction

Dental cavity identification has always been challenging because of the amount of information acquired from various radiography images. Several techniques have been developed to enhance image quality to detect cavities more quickly. When analyzing medical images, deep learning has emerged as the preferred methodology (24). As a result, this study examined several of the most relevant publications under related works based on the factors below.

- ✓ Ascertained the techniques and formulas they employed for categorization and tooth decay identification.
- ✓ Addressed about the many models they employed.
- ✓ Explained in detail how they stack up against one another in terms of evaluation and system performance.
- ✓ Examined the methods for extracting picture features, preprocessing, sourcing datasets, and fine-tuning their models.
- ✓ Discussed about the models' limits, validation, correctness, and size of the dataset. When compared to studies on other diseases, the amount of dental cavity-related ailments may be less.

In general, we have seen a few research articles and systematic reviews in the field of identifying and diagnosing dental cavity illness. The table at the end of this chapter summarizes every reviewed work on earlier research. Additionally, these chapters, discussed ideas, hypotheses, approaches, and conclusions pertaining on the title, examined, and assessed the advantages and disadvantages of earlier research.

2.2 Image Classifications Definitions

The technique of classifying an image based on its visual information is known as image classification in computer vision. In this kind of supervised learning, algorithm is trained on a labeled dataset of images and then used to predict the label of unseen images. The goal of image classification is to teach the model to recognize and accurately categorize different items or patterns in photographs. Identifying a collection of target classes (i.e., objects to identify in photographs) requires supervised learning (25).

2.3 Types of Image Classifications

The kind of image categorization methodology used will depend on the nature of the challenge. Binary, multiclass, multilabel, and hierarchical are these (26) .

2.3.1 Binary Image Classifications

In binary classification, unknown data points are divided into two groups and images are labelled using an either-or logic. This type can be employed to manage many more yes/no problems, such as classifying benign or malignant cancers, analysing product quality to determine whether it has faults, and many other tasks requiring judgment calls (27).

2.3.2 Multiclass image Classifications

Multiclass classification, as the name implies, divides objects into three or more classes, whereas binary classification is used to discriminate between two classes of objects (28). A sort of machine learning assignment known as multi-class image classification involves classifying an image into three or more groups. Multi-class classification works with several categories as opposed to binary classification, which only deals with two classifications.

2.3.3 Multilabel Classifications

Multilabel classification permits the object to be allocated to numerous labels, in contrast to multiclass classification, which assigns each image to a single class. For instance, if there are multiple colours in an image and you need to categorize them (29).

2.3.4 Hierarchical Image Classifications

The process of categorizing classes into a hierarchical structure based on shared characteristics is referred to as hierarchical classification. A lower-level class is more specific and detailed, whereas a higher-level class encompasses broader categories (30).

2.4 Applications of image classification

Image categorization has gained a lot of attention for good reason; it is revolutionizing a number of industries, including retail, security, autonomous driving, agricultural, and medical. Let us examine why it gained such traction in these industries (31).

2.4.1 Medical images

It is no secret that the healthcare industry has been widely implementing computer vision throughout its activities. In one of our case studies, we share how Super Annotate helped Orsi, Europe’s leading advocate for robotic and minimally invasive surgeries; achieve 3x faster annotation for their surgical image data. It does not stop there, as there are several such cases when medical companies streamline their processes by just trusting industry-lead annotation companies to automate their data processes (32).

2.4.2 Autonomous driving

Autonomous driving carries a leading role as an image classification user. The cameras and sensors attached to the cars can detect objects on roads, mostly due to machine learning algorithms working on massive amounts of datasets of driving scenarios. The classifier helps to respond to the surroundings by identifying whether the object is a pedestrian, vehicle, road sign, or tree (33).

2.4.3 Agriculture

Classifying image is used in agriculture to monitor plant growth, diagnose pests and illnesses, classify photos of crops, and generally make farmers' lives easier. It is similar to having a farmer's sixth sense that can detect changes in the health of crops and soil, helping them make more, informed decisions about irrigation fertilization, and pest control (34).

2.4.4 Security

Over the past ten years, as classification technology has advanced and become more widely available, its application in security office has grown. It began with surveillance systems, which were used to examine video material that had been captured and spot possible security risks (35).

2.4.5 Social media analysis

Image classification is used in social media platforms to automatically generate image tags, recognizes face, and filter in appropriates contents (36).

2.5 Tooth Cavity Diseases

Cavity, also referred to as dental caries or tooth decay, are affected by a types of different factors, such as oral bacteria, eating frequently, drinking sugary drinks, and not brushing your teeth enough (37). Numerous studies have attempted to illustrate the prevalence of dental cavity problems, especially in Ethiopia (15). The most prevalent dental cavity conditions in their various stages were reported in this study. Four commonly occurring tooth cavity stages were evaluated in this study:

2.6 Overview of the stages of tooth cavity

Tooth deterioration happens gradually and in phases. When it comes to cavities, the early stages are readily treatable, while the latter stages may pose a risk to your overall health. Here is a closer look at how a cavity formed and on which part of tooth structure happened (enamel, dentin and pulp/root).

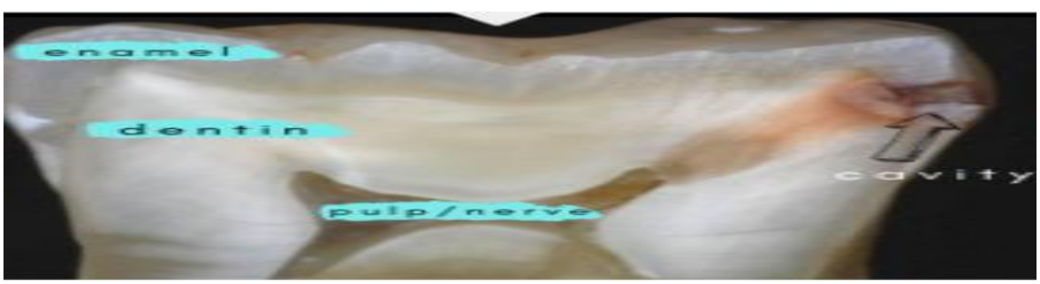

Figure 1 General overview of stages of tooth cavity

As time passes, tooth decay progresses through the five stages. The following are the stages of tooth cavity developed from one stage to the other.

2.5.1. Demineralization

The early stages of decay result from prolonged exposure to acid produced by germs present in dental biofilm. Enamel, the minerals composing teeth, gradually erodes when plaque is allowed to remain and brushing is neglected. Small white patches on the teeth, indicating a loss of minerals and enamel, serve as an indication of the beginning phases of decay (38).

Figure 2 First stages of tooth cavity (Demineralized teeth with white spot)

2.5.2 Enamel Decay

In the second phase of tooth decay, there is a more pronounced erosion of enamel. The presence of brownish areas, which individuals with white spots from mineral loss may observe turning brown, signifies an even greater depletion of minerals and enamel. Those with stage 2 tooth decay are at a higher risk of developing cavities due to the weakened enamel (39).

Figure 3 Stage 2 tooth cavity (Enamel decay with dark spot)

2.5.3 Dentin Decay

Dentin is the tissue situated beneath the enamel in teeth. When enamel wears away, dentin becomes susceptible to degradation. Dentin degrades at a faster rate than enamel due to its softer nature and increased susceptibility to the acidic byproducts of plaque bacteria. Dentin comprises tubes linked to the nerves of the teeth, so its deterioration can lead to sensitivity (38).

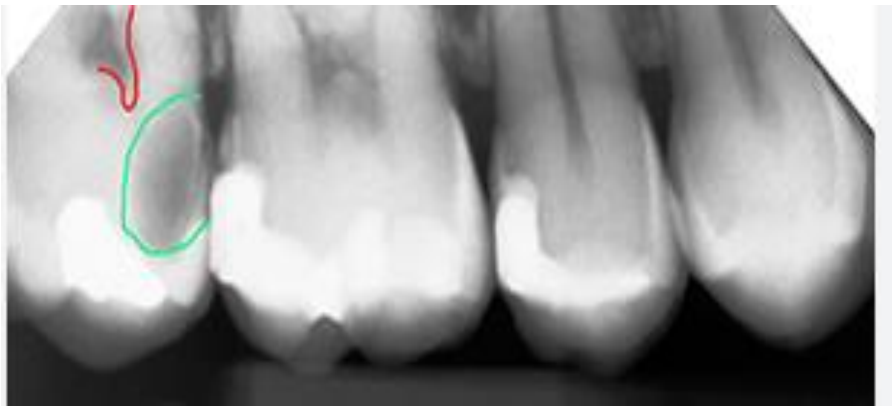

Figure 4 Dentin decay overview

2.5.4 Pulp Damage

When dentin undergoes complete deterioration, the pulp, which is the innermost part of a tooth, becomes exposed. The pulp consists of blood vessels and nerves. Decay affecting the pulp can lead to discomfort, swelling, and heightened sensitivity. Early identification of pulp damage allows for repair; however, advanced damage may necessitate root canal therapy or tooth extraction (40).

Figure 5 Pulp damage overview.

2.5.5 Abscess

This represents the ultimate phase. When the pulp experiences severe damage, bacteria have the potential to propagate and thrive within the tooth near blood vessels and nerves. This can lead to the formation of an abscess, a collection of pus near the tooth's base, accompanied by intense inflammation. Tooth abscesses induce severe, radiating pain across the jaw. Antibiotics and tooth extraction are essential treatments for addressing these conditions.

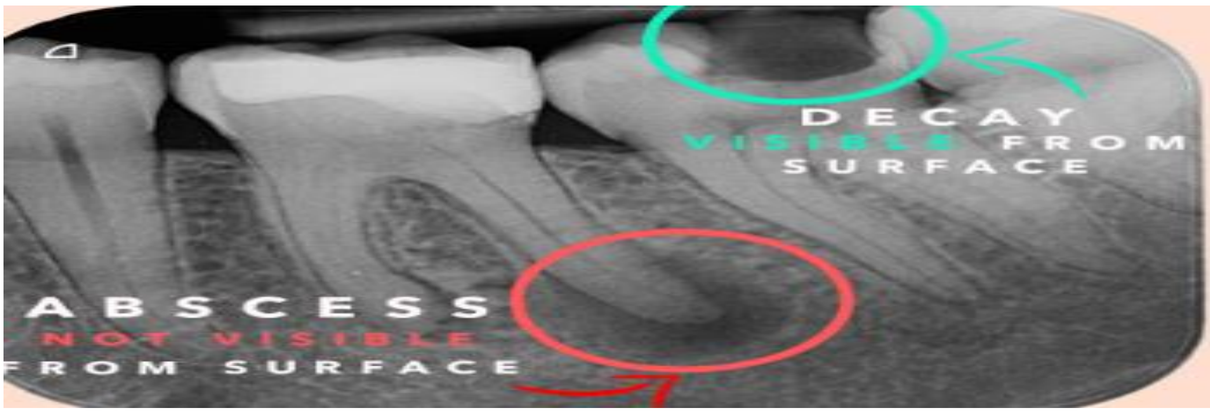

Figure 6 abscess Tooth cavity stages.

2.6 Current Approaches for Diagnosis of Tooth Cavity Diseases

Historically the duration of the tooth cavity problem, the location of the onset, the characteristics of the spread, and the size of the lesion, as well as any aggravating or triggering symptoms (caries, discolor, pain), all provide important information for diagnosis. Larger decays might exhibit telltale signs and symptoms including toothache, pain that comes on suddenly, or pain that has no obvious reason. The sensitivity of teeth, varying from mild to intense discomfort, is experienced when consuming sweet, hot, or cold foods and drinks. The method employed for diagnosing existing dental cavity conditions, along with past and present general medical diagnoses, is crucial in the accurate assessment of tooth cavity illness. The treatment for your cavities and the appropriate course of action will be determined by the severity of the condition and your individual circumstances (41).

2.6.1 Asking about tooth pain and sensitivity

Most commonly, shattered teeth result in sensitive teeth. Yet, other issues like gum disease, deteriorated fillings, cavities, and chipped or fractured teeth can also occasionally result in dental discomfort.

2.6.2. Visual Examining

A dental check-up involves an assessment of both the teeth and gums. A standard dental visit encompasses three main components: a dental cleaning to eliminate plaque, a sticky film harbouring bacteria, and X-rays of your teeth taken at specific intervals based on the condition of your teeth (42).

2.6.3 Probing your teeth with dental instruments

The purpose of the dental probe is to gently probe your gums and teeth. When in use, the probe is placed against the inside of your teeth and gums to feel for soft areas. If the probe is exposed to an area that feels soft this could be a sign of gum disease or tooth decay.

2.6.4 Looking at dental X-rays

X-ray has a big role in the medical diagnosis to treat and manage the diseases. It simply shows the hidden layers and tissues of internal human body. Between the pulp and the enamel is the dentin layer (43).

2.7 Deep Learning in Medical Image

The aim of this chapter is to provide a comprehensive examination of machine learning algorithms applied to issues in medical image analysis, focusing on recent research and potential future directions for the field. This is achieved by presenting the latest developments in deep learning techniques and foundational concepts in the domain of medical image processing and analysis (43). The deep learning network is considered a vital approach for the future, presenting compelling solutions to challenges in medical image pre-processing. There has been a significant surge in the application of deep learning in scientific computing, with many organizations dealing with intricate issues choosing to employ its algorithms regularly (18).

Lately, there has been a notable progress in deep learning, with these techniques playing a pivotal role. Analysis methods based on deep learning effectively extract information from images, providing a swift and efficient representation. This makes it more convenient and quicker for healthcare professionals to identify conditions, anticipate the risks of illnesses, and take prompt preventive measures (43).As a result, the algorithm based on deep learning is being used extensively these days to address a variety of issues in the field of medical imaging. One instance is the radiology process of identifying anomalies or diseases from X-ray images and categorizing them according to various disease types or severity levels (44).

The introduction of deep learning technology has effectively addressed these issues, providing a high level of accuracy in response and allowing human professionals more time for other valuable activities. Nevertheless, the advancement of this technology does not imply that doctors, particularly radiologists, will become obsolete. Image classification is one aspect of computer vision used to assist computers in comprehending human input and responding accordingly (45). CNN is a good fit for picture categorization because of this method since it comprehends user input and generates replies that are pertinent to the context (46). The convolutional layer manages convolution operations with a small set of uniformly sized filter maps. Additionally, the output from this layer is directed to the pooling layer, responsible for reducing the size of subsequent levels. CNNs, or ConvNets, are a crucial component of deep neural networks frequently utilized in deep learning, particularly for visual perception assessment (47).

2.7.1 Deep Learning Algorithms for image classification

These functions are designed to automatically extract relevant features from raw image data and use them to categorize photos into different groups (48).

2.7.1.1 Convolutional Neural Networks (CNNs):

The classification of images is a common application for CNNs. Convolutional layers are employed to extract pertinent information from photographs, which are then pooled to minimize spatial dimensionality. CNNs are renowned for their capacity to identify spatial connections and local patterns in pictures (43).

2.7.2 Residual Neural Networks (ResNet):

One kind of convolutional network design that makes use of leftover relationships is called ResNet. Through these connections, the network can learn more intricate and detailed representations by allowing input from earlier levels to bypass later ones (49).

2.7.3 DenseNet:

An alternative design variation of CNN is known as DenseNet, where each layer is directly connected to every any layers in a feed-forward manner. This extensive interconnection enhances accuracy and facilitates feature reuse and gradient flow (50).

2.7.4 VGGNet:

A deep convolutional neural network with tiny 3x3 filters is called VGGNet. It is straightforward to comprehend and apply because of its standard architecture. VGGNet performed exceptionally well across a range of picture categorization tests (51).

2.7.5 InceptionNet:

The idea of inception modules—which employ several filters of varying sizes in tandem to capture features at different scales—was first presented by InceptionNet, This architecture maintains excellent precision while assisting in the reduction of parameters. These are but a few instances of picture classification techniques utilizing deep learning algorithms. With the aim of attaining precise and effective picture categorization, each algorithm has a distinct design and variants (52).

2.8 Deep Learning Architectures for image classification

Three layers of artificial neural networks make up the deep Learning architecture, which is extensively used to develop picture categorization. These networks are capable of learning to comprehend normal language, carrying out challenging tasks, and producing responses that like those of a human (26).

The input layer, which supplies data from the external environment to the hidden strata, has an equal number of neurons as input variables in the data it processes. Data is fed from the input layer to the hidden layer, which processes the data and extracts relevant features using computer vision algorithms. We may have one or more hidden layers; it is difficult to determine how many neurons and hidden strata are included in the model. Nevertheless, it is feasible to experimentally ascertain the ultimate number of the hidden layer by trial and error depending on the best result during model training (48).

The output's result is calculated in the output layer, which is the last layer. The main job of the output layer is to compute the result after processing inputs sent in from layers above it using its neurons. When creating picture categorization, the output layer's neuron count matches the target class that the user has in mind.

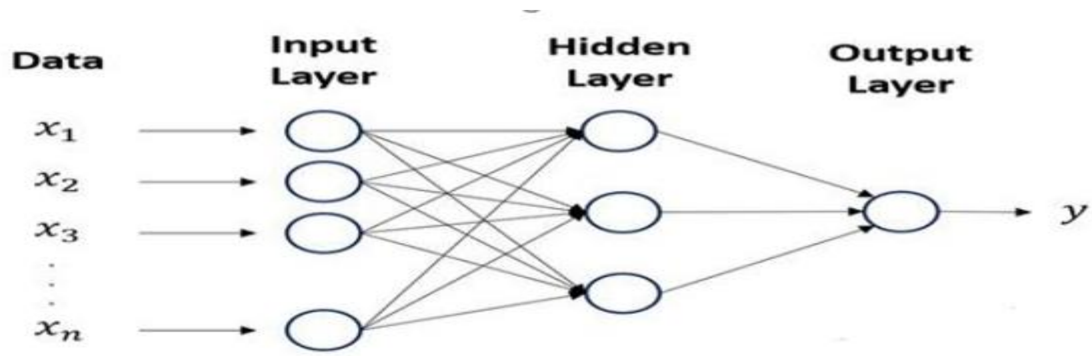

Figure. 7 Deep neural network architecture.

2.9 Related work

By examining a number of similar studies, this issue also highlights what has been done by others and the gap that has to be filled by the suggested effort. Compared to other medical conditions, the amount of research on AI-related oral cavity illnesses may be minimal. Various scholars have studied picture categorization for different purposes in different parts of the world. Several researchers that were involved in our work, particularly those who used deep learning techniques and the tools and procedures they employed, are discussed in this section, along with the conclusions of each study that we looked at. Advanced oral healthcare conditions are made possible by the accurate and easily accessible detection of dental caries using intraoral photos employing DL. Additionally, this computer-aided diagnostic (CAD) method is a consistent and dependable helper, because of lack of dataset size for DL technology. Different researcher has described dental cavity disease factors and their Prevalence as the following.

The work Ethiopian dental caries and related factors: meta-analysis and comprehensive review was carried out, according to (Zewdu.T Abu. M. et al.) tooth cavity and its factors in Ethiopia (15) (13).

Ali MM, Geleto A, and Sinba E. Patients who visit Shashamane Comprehensive Specialized Hospital have dental caries and related issues (53).

Moges Wubneh AbateID1 *, Adane Birhanu Niga and et.al. investigated the prevalence of dental caries and related variables among Ethiopian primary school students in 2021. Dental caries was more common and a common public health concern among schoolchildren (54).

et.al. 2021 Apurva Sonavane "Classification of Dental Cavities Using Convolutional Neural Network "states: The teeth-related Kaggle dataset was used in the study (38).

- **Dataset**: The dataset includes visual depictions of images with cavities and images without cavities. The dataset consists of 74 photos, 60 of which are for training and 14 for testing.
- **Pre-processing and image augmentation:** The dataset contained images in JPG format. ImageDataGenerator from the keras.preprocessing.image in Python was employed, incorporating random horizontal flipping, and 20% of the images from the training set were used for validation.
- **Architecture:** Ten layers make up the Sequential model they have developed. A learning rate of 0.001 and 30 epochs were applied to the training dataset.
- **Results**: With a learning rate of 0.001, our CNN model was developed with binary cross entropy loss to classify dental caries and non-caries. Nevertheless, adding more photos to the dataset will improve the accuracy of the model. By adjusting the hyper-parameters of the model, they evaluated it and were able to get a maximum accuracy of **71.43**%.

By F. Oztekin, Katar. O, and et al. in the year 2023. An Explainable Deep Learning Model to Prediction Dental Caries Using Panoramic Radiograph Images. (55)**.**

- **Datasets:** A total of 1160 dental photos with decay and 1040 without it were collected from all available panoramic photos. During the test phase, they used 300 photos with cavity and 300 photographs without them.

- **Data augmentation method**, In the train and validation levels, there were 6635 samples total a combination of caries and non-caries.
- **System Model**: To find the best pre-trained model for the caries detection job, they examined EfficientNet-B0, DenseNet-121, and ResNet-50.
- **The model**: The evaluation involved the examination of complete panoramic images from 562 subjects. The results obtained from all three models were remarkably consistent. However, the ResNet-50 model exhibited a slight superiority compared to EfficientNet-B0 and DenseNet-121.
- **Result**: The model yielded 92.00% accuracy, 87.33% sensitivity, and 91.61% F1-score.

Under the title "Deep Learning for Caries Detection and Classification", Luya Lian, and et.al published their work in 2021 (19).

- **Trained models: DenseNet121** has been developed to detect the expansions of caries lesions. During model training, they employed transfer learning to get around the dataset's short size and the pertained DenseNet121 network to the target DenseNet121 model applied.
- **Evaluation Methods:** Two methodologies are utilized—the Classification involves the use of DenseNet121, and Segmentation involves the application of nnU-Net.
- **Result**: DenseNet121 showed an overall accuracy of **0.957**, for caries classification respectively.

According to the study in 2022 by (E.Y., Cho, H., *et al).* "**Caries detection with tooth surface segmentation on intraoral photographic images using deep learning"** (56).

- **Datasets:** The training (1638), validation (410), and test (300) datasets received random assignments of images.
- **Results**: Segmenting the tooth surface through CNN improved the accuracy and the area under the receiver operating characteristic curve for the caries image classification algorithm from 0.758 to 0.731, respectively.
- **Methods and model**: In this prospective study, artificial neural networks, namely U-Net, ResNet-18, and Faster R-CNN, were utilized.

Zhu H, Cao Z, Lian L, Ye G, Gao H, and Wu J on January 7, 2022, entitled a " deep learning technique, to segment multi-stage caries lesions" (57).

- **Datasets: 3127** well-defined caries lesions, comprising superficial, intermediate, and deep caries.
- **Model**: They constructed **CariesNet** as a U-shape network with the additional full.
- **Result**: Experiments show that **93.61%** accuracy in the segmentation of three different of caries.

In December 2022, (Tugba Ari 1 , Hande Sa ˘glam 1 , Hasan Öksüzo ˘glu , and et.al) Perform a diagnostic evaluation on periapical radiographs with an AI model based on Convoluted Neural Networks (CNNs)." (58).

- **Datasets**: using 1169 datasets adult periapical radiographs, which were labelled in CranioCatch annotation software.
- **Method**: Deep learning was performed using the U-Net model implemented with the PyTorch library. The AI models based on deep learning models improved the success rate of carious lesion, crown, dental pulp, dental filling, periapical lesion, and root canal filling segmentation in periapical images.

In 29 May 2022 (Mai Thi Giang Thanh, Ngo Van Toan and et.al) they investigate entitled on Deep Learning Application in Dental Caries Detection Using Intraoral Photos Taken by Smartphones.'

Materials and methods: They used training datasets of **1902** photos of the smooth surface of teeth taken with an iPhone 7 from 695 people.

Models: They used four deep learning models such as Faster R-CNN, You only look Once (YOLOV3), RetinaNet and Single –Shot Multi-box Detector (SSD).

Objectives: Segmenting the image datasets and detected the presence of caries on segmented images.

Table 1 Summary of Relevant work

No	Author name and year	Models applied	Accuracy they achieved	Dataset size	Limitations
1	et al 2021 Apurva Sonavane	Deep learning approaches.	**71.43%.**	**74** images	Limited to small datasets.
2	Published in 2023 by F. Oztekin, O. et al.	Efficient, Net-B0 DenseNet and ResNet50 models	**92.00 %**	**2200** X-ray images	A limited accuracy with efficient models.
3	2021 (by Luya Lian, Tianer Zhu, et.al)	A convolutional neural network (**Densenet121**)	**0.957%**	**1160** images	Only established validation and training (1071) and a test dataset (89)
4	**2022** by Park, E.Y., Cho, H., et al .	ResNet-18, and Faster R-CNN, was applied.	**0.813%**	**2348** images	small dataset low accuracy
5	**2022** By Zhu H, Cao Z, et.al	Deep learning approaches	**93.61%**	**3127** images	If use two or more may get high result.
6	Luo C, et.al	semantic segmentation model, DeepLabv3+	**90.0%**	**194** images	Small dataset.

7	Ari. T, Sağlam. H. et al.	Deep learning	**0.82%**	**1169** images	used a very small dataset.
8	2022 by (Mai Thi Giang and et.al)	Faster R-CNN, RetinaNet and Detector (SSD).	**87.4%**	**1902** images	Low segmentation accuracy.

2.10 Critics Summary

Diverse works have been undertaken using a variety of approaches, as the previous discussion demonstrated. However, there are not many standard methods that can be used with any of these approaches. Our previous investigation primarily focused on utilizing deep neural networks, specifically pre-trained CNN models, to identify the stages of tooth cavities. Despite the wealth of AI-driven dental research conducted thus far, the problem of identifying tooth cavity stages has remained unaddressed. Consequently, we have chosen to bridge this gap by utilizing deep learning algorithms to classify the stages of tooth cavities.

Within the realm of related studies, certain limitations have been observed. Most of the reviewed papers attempt to detect the caries lesion and segmentation which based on the only presence of cavity and others are also classify caries lesion which is not covered all the stages of cavity with the less amount of image datasets. Therefore, the previous works has not totally solved some stated problems in current dentistry department. Furthermore, it has been observed that there are no safeguards against model overfitting, which leads to models that work incredibly well on training data but poorly when trying to predict fresh data. Furthermore, in the majority of research, the use of specific feature extraction algorithms has led to low accuracy and significant time complexity. With the help of our suggested strategy, we have solved some of the challenges raised by the prior research.

CHAPTER THREE

3. RESEARCH METHODOLOGY AND TOOLS

3.1 Chapter Overview

This chapter consolidates the methodologies and tools employed in developing the proposed model. The study's objectives were achieved through the implementation of specific methods and resources. This section delves into the strategies utilized to meet the study's goals, encompassing processes such as data collection and annotation, image pre-processing, data segmentation, feature extraction, as well as model train and test. As stated in the title, we employed a variety of methodologies, datasets, assessment criteria, and strategies to address the issue of image classification using deep learning models. Many obstacles are linked to this work in this chapter, such as, perspective variation, dataset limitation, image deformation, visual concealment, illumination circumstances etc.

3.2 Research Design and Experimental setup

In this study the experimental research design have used to solve the proposed problems we integrated computer vision and deep learning techniques. The researcher was followed a scientific and systematic method to collect relevant data from experts. Experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand the causal process. It is used by the researchers for identifying the cause and observes which powerful tool the diagnostic of the results is. Generally the scientific methodology for image classification involves a systematic approach to designing, implementing, and evaluating the performance of image classification algorithms. Below is a general outline of the scientific methodology for image classification we applied in our study:

- ✓ Problem Definition: We clearly defined the problem related with determining the stages of tooth cavity diseases address through image classification. We also Specify the types of images, the classes we want to classify, and the objectives of the classification task.
- ✓ Data Collection: In our work we have collected a representative dataset for training and testing the image classifier which described in 3.2 sections.

- ✓ Data Preprocessing: we apply deep learning techniques which are used for clean and preprocess the image data.
- ✓ Feature Extraction: In this step we chosen deep learning techniques which are used for transforming raw pixel data into a format that the machine learning algorithm can understand.
- ✓ Model Selection: We have chosen a suitable deep learning that is pre-trained model for image classification based on the complexity of the problem and the size of the dataset.
- ✓ Model Training: We have train the selected model using the labeled training X-ray dental image dataset. This involves adjusting the model parameters to minimize the difference between predicted and actual class labels.
- ✓ Model Evaluation: Evaluate the trained model using a separate test dataset that the model has not seen before. The common evaluation metrics accuracy, precision, recall, F1 score, and confusion matrices were applied.
- ✓ Hyper parameter Tuning: In our work we have chosen hyper parameters which are used for model to optimize its performance.
- ✓ Interpretability and Visualization: Analyze the model's predictions and visualize the learned features to gain insights into how the model is making decisions. This step is important for understanding the model's behavior and addressing potential biases.

In this study the experimental research design we followed are a structured approach, whereby the researcher manipulated and controls variables to comprehend the underlying causal processes.

3.3. Data collection methods

Preparing datasets is a prerequisite for developing the proposed system. Preparing datasets is a prerequisite for developing the proposed system. The datasets used in this work are made up of medical imaging which has been collected from Jimma University Specialized hospitals from dentistry department and Waliin medium dental clinic at Jimma town specifically at merkato. The total collected datasets for this study are 4725 with four classes of X-ray tooth cavity images. With an emphasis of on dental cavity imaging, panoramic X-ray radiography was used to obtain these images. The decision to use this radiographic device was made in part because high resolution cameras for X-rays are widely available. Final, all the collected images stored in the

(.JPG) file format, with 24 bits per pixel. Among these images, 3541 were cavity images, while the remaining 1184 were X-ray images of healthy teeth. While collecting the dataset, we encountered a significant challenge in obtaining the desired amount of data. Unlike other health medical datasets, dental datasets are scarce in both government and non-government health institutions. This scarcity is primarily due to the lack of additional digital machines and software utilized for this purpose.

Table 2 the total results of collected datasets

No	Dataset contents	Dataset Size
1	Training and Validation Datasets	3817
3	Test Datasets	456
3	Validation Datasets	452

3.4 Dataset preparation Methods

A dataset that has been divided for model training and testing before the data is added to the network. Data splitting best practices generally recommend dividing the data into 80–20 percent train and test sets, respectively. Of the 20%, 10% is utilized for validation and the remaining 10% is used for testing. The network was trained on a train set, and a validation set was used for model selection, parameters adjustment, and performance monitoring. The performance of the finished model was then evaluated once using a test set.

Table 3.2 Overall Dataset Splitting

No	Classes	Training Dataset (80%)	Testing Dataset (10%)	Validation Datasets (10%)
1	Dentin decay	983	91	117
2	Enamel decay	931	143	104
3	Healthy	910	125	114
4	Pulp Decay	993	97	117
	Total	**3817**	**456**	**452**

3.5 Transfer Learning Techniques

Transfer learning is a technique in machine learning and deep learning where a pre-trained model, typically trained on a large dataset for a specific task, is used as the starting point for a new task. Instead of training a model from scratch, transfer learning leverages the knowledge gained from the pre-training on a source task to improve the performance on a target task. Transfer learning is particularly useful in scenarios where labelled data for the target task is limited (59). To implement the concept of transfer learning, we make use of "**pre-trained models**". This pre-trained models is a technique in which we increase the existing dataset with transformed versions of the existing trained biases and weights. Here are some key reasons why we used transfer learning in our work:

- ✓ **Limited Data for Target Task**: In many real-world scenarios, obtaining a large labelled dataset for training a model from scratch on a specific task may be impractical or expensive. Transfer learning allows leveraging knowledge from a source task, where more data is available, to boost performance on the target task.
- ✓ **Feature Learning:** Pre-trained models, especially deep neural networks, learn hierarchical features from raw data during the pre-training phase. These learned features capture general patterns and representations of the data.
- ✓ **Effective Use of Computational Resources:** Training deep neural networks from scratch can be computationally expensive. Transfer learning enables the reuse of pre-trained models, making efficient use of computational resources.
- ✓ **Improved Convergence:** Transfer learning often leads to faster convergence during training on the target task.

3.6 Data Preprocessing Techniques

Pre-processing aims to improve the photos quality so that we can analyze it more successfully. Preprocessing enables us to enhance certain attributes that are crucial for the application we are working on and remove undesired distortions. These attributes may vary based on the intended use (60).

3.6.1 Normalization

Projecting picture data pixels (intensity) to a preset range (typically (0, 1) or (-1, 1)) is also known as data re-scaling. This method is frequently applied to many data formats; you want to normalize each one so that the same techniques may be applied to it (61).

3.6.2 Contrast Enhancement

The objective of contrast enhancement methods is to enhance the contrast of an image, making it easier to distinguish specific image features. Such techniques find applications in surveillance and medical imaging. In our study, we implement several standard contrast enhancement techniques, including contrast stretching, adaptive histogram equalization, and histogram equalization (62).

3.6.3 Image Resizing

The size of an image can be changed by using image resizing techniques. Resizing an image allows you to adjust its aspect ratio, size, and other parameters. Bilinear interpolation, bicubic interpolation, and nearest neighbour interpolation are a few common methods for scaling images (63).

3.6.4 Color Correction

The color balance of an image can be adjusted using color correcting procedures and use applications like photography, where an image's color fidelity is crucial, color correction is significant. We frequently used color transfer, white balance, and grayscale world assumption as color correcting procedures.

3.7 Feature Extraction approaches

All of the data we gathered in real life were substantial volumes. We require a procedure in order to comprehend this data. It is not possible to process them manually. This is the point at which we consider feature extraction. In order to resolve this issue, we turned to some of the largest machine learning projects or the trendiest and most well-liked fields, such deep learning, where you may use pictures to create an object identification project (64). In order to anticipate the ultimate results of test datasets, our concepts use various convolutional layers to extract various types of information from inputted image datasets, such as image size, color, location, and shape.

3.8 Model Selection methods

Automated learning employs algorithms to analyse data, derive insights from it, and make informed decisions based on the acquired knowledge. In order to create "artificial neural network" that is capable of autonomous learning and wise decision-making, deep learning uses layered algorithms (65). A machine model functions as a trained instrument with the ability to recognize particular patterns. “Supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning are the four types of machine learning algorithms”.

Since labeled data or data with established target classes were available, a supervised technique was used in this investigation. Using the prepared dataset as a basis, a deep learn model was chosen according to the suggested methods. The dataset was prepared using the JPEG image format, as specified in the data preparation technique. This dataset was categorized using the labeled classes that the dentists provided. During the model training process, these categories functioned as the predictive classes. The fact that the dataset included many labeled classes highlights the significance of using a classification with multiple classes focused model selection criterion. Recent developments in the field indicate that deep learning algorithms perform better in multiple class classification than machine learning techniques (6). Following a comparison of machine and deep learning, we found that deep learning outperforms the latter in terms of multiclass classification accuracy. Diverse neural network topologies are used for diverse purposes in the field of deep learning. These include, among others, Convolutional Neural Networks, Deep Neural Networks, Recurrent Neural Networks and Artificial Neural Networks. Out of these choices, the CNN and two pre-trained CNN models—VGG16 and InceptionResNetV2 have been used to create the suggested system.

3.8.1 Convolutional Neural Network

In this paper work, we especially address the problem of selecting the appropriate convex neural network model for the multiclass of normal contrast medical images. We conducted a comparison of the accuracy, evaluation metrics (F1 score, recall), and architectures of VGG16, CNN, and InceptionResNetV2 using a selected subset of tooth cavity images at different stages. CNN's primary advantage is in its ability to autonomously recognize pertinent elements without requiring human oversight. CNNs have been widely used in many different domains, such as speech processing, face recognition, computer vision, etc. Convolutional neural networks (CNNs) are the foundation of the CNN classifier, a method used for image classification. Its goal is to accurately classify photographs into specified groups by identifying pertinent elements in incoming photos and matching them to the corresponding groups.

In order to apply CNN for image pre-processing, we must first specify its architecture, preprocess the input images, train the model using labeled data, then evaluate its results using test images. The trained CNN can then use the attributes it has learned to categorize fresh images.

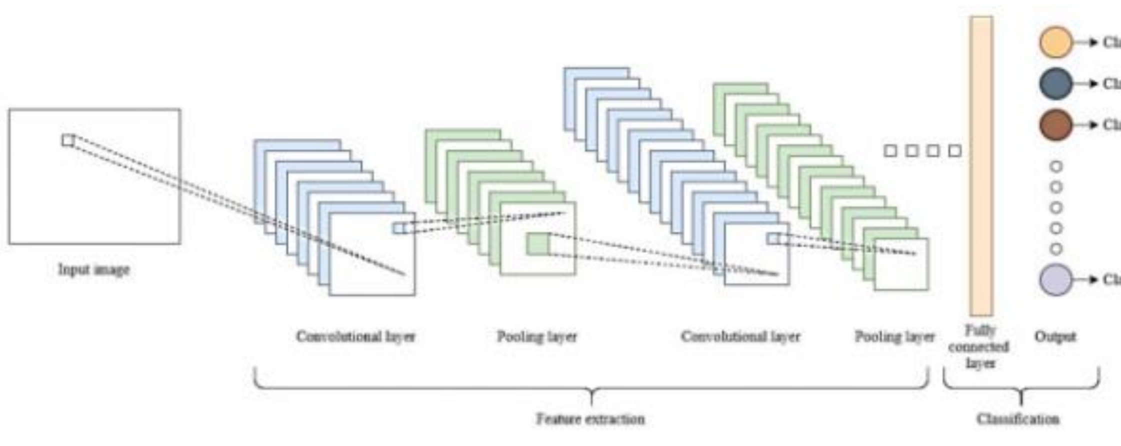

Figure 8 CNN Basic Architecture for image Classification.

3.8.2 VGG-16 (Visual Geometry Group)

To prevent data overfitting in our trials, we first used the pre-trained VGG-16 convolutional neural network model, which was improved by freezing parts of the layers. This was especially important for our chosen image set, which is incredibly small. The VGG model is a popular choice for classifying images. With respect to the network's input picture, its dimensions are (224 × 224 × 3) (66). Additionally, it consists of 16 convolutional layers that feed into a fixed-size filter in the (3 × 3) and 5 layers of Max grouping that cover the entire network in size (2 × 2). [44][69].

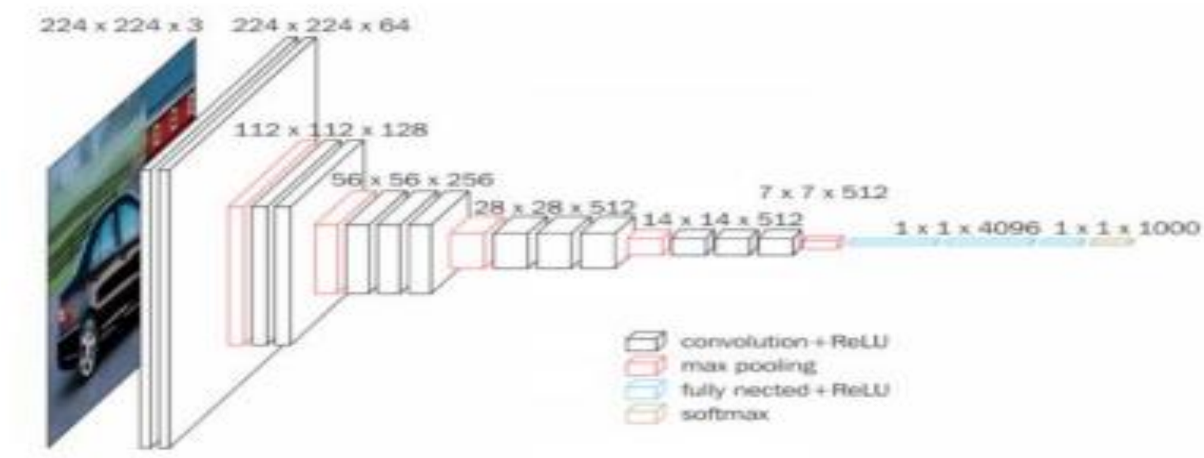

Figure. 9. VGG-16, model architecture

3.8.3 Inception-ResNet-v2

A convolutional neural network called Inception-ResNet-v2 was trained using over a million pictures from the ImageNet collection. The biggest improvements in image recognition performance have been mostly attributed to ResNet and Inception. offers excellent performance in recent years at a comparatively cheap computational cost. The Inception architecture is combined with residual connections to create Inception-ResNet (67) .

Residual Inception blocks

- ✓ A filter expansion layer (1 × 1 convolution without activation) follows each initiation block. This layer is used to scale up the dimensionality of the filter bank prior to addition to match the input's depth.
- ✓ Batch-normalization is applied exclusively to the traditional layers in the Inception-ResNet model; it is not applied to the summations.

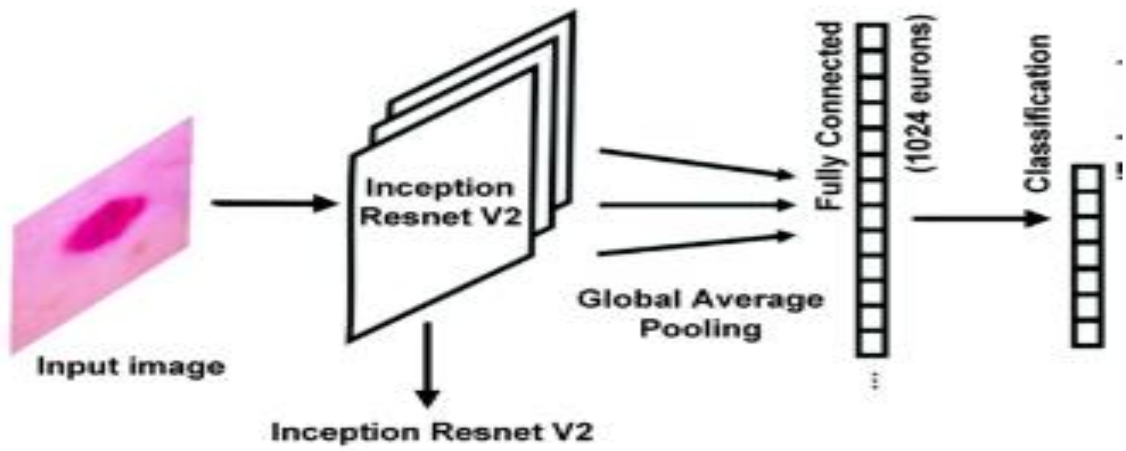

Figure. 10. InceptionResNetV2 architecture for the image classification

3.9 Hyper-parameters

Algorithms for machine intelligence have been widely used in many different fields and areas. A machine-learning model's parameters require careful attention in order to adjust it to various problem scenarios. The accurate selection of hyper-parameter configuration significantly influences the performance of machine learning models (68). Modern supervised machine intelligence algorithms necessitate the pre-configuration of hyper parameters prior to their execution. In the realm of deep learning, an abundance of parameters can be adjusted to attain optimal outcomes. This procedure, known as fine-tuning, is hindered by time constraints, making it impractical to exhaustively explore all parameter combinations. The wide range of possible values and the length of time needed to complete even one experiment serve as evidence that choosing appropriate parameters is more of an art than a science. To make matters worse, there are no clear guidelines about which configuration process to use. Therefore, the only method is to use the trial-and-error technique, which means that several configurations must be investigated. In our study, we used a manual method to find most of the hyper-parameters through a sequence of trial experiments. The activation function, batch size, epoch, loss, optimizer, learning rate, and the quantity of neurons in each layer are all included in this set of parameters. It is important to keep in mind, nevertheless, that different models have different parameter setup arrangements.

3.9.1 Activation Function.

The mathematical formulas known as activation functions regulate a neural network's output. Each neuron in the network receives the function after computing the "weighted sum (Wi)" of each neuron's input (xi), adding a bias, and deciding whether to fire the neuron based on whether or not its input is significant for the model's prediction. In deep learning, activation functions come in a variety of forms. For the recommended system, we used the following activation functions:

- ✓ **ReLU (Rectified Linear Unit) activation functions** at the input layer because it allows the model to handle large amounts of sparsity in the input data, which can lead to inefficient computation and slow training times. In addition, we use ReLU in the hidden layer due to its computational efficiency, better convergence properties, and avoidance of the vanishing gradient problem.
- ✓ **Softmax activation functions** in the layer of output. This activation function is advantageous in managing multiple class predictions, which is why we chose it.

3.9.2 Batch size:

An internal model parameter that sets the minimum type of samples that must be processed to update the model's internal parameters. The batch size is the amount of data the model consumes in a training session.

3.9.3 Epoch.

An epoch is a hyper-parameter in the learning algorithm that determines how many times the training dataset will be processed. Within an epoch, each sample in the training dataset has the opportunity to adjust the internal model parameters once.

3.9.4 Loss function.

The model's performance in completing the desired task for the network is assessed using the loss function. Compares the target and anticipated output values to see how well your neural network model is performing. By applying the Categorical cross-entropy function during the training process, our goal is to reduce the difference between the target and predicted outputs.

3.9.5 Optimizer:

Hyper-parameters are used to adjust the learning rate and weights to reduce losses. The Adam optimizer was used in this work because of its capacity to display fast convergence features and streamline the learning rate. It is a suitable optimization approach for sequential data formats since it also predicts the initial mean and secondary variance to control the coefficient adjustments.

3.9.6 Learning rate:

A well-chosen learning rate is crucial for optimizing/modifying the offsets and weights. The system becomes unstable if the learning rate is too high because it is simple to surpass the extreme point. Conversely an excessively low learning rate results in an excessively protracted training period. Starting with $\eta=0.01$, we can approximate the order of magnitude. We used experimentation to determine an optimal learning rate in the study task.

3.10. Model Overfitting Handling Approaches

When a model has a high variance—that is, when it performs well on training data but inaccurately on the evaluation set—overfitting takes place. The model retains the training dataset's data patterns, but it is unable to generalize to new samples. Overfitting typically occurs in machine learning techniques when: The training data is unclean and has invalid values in it. The model is unable to generalize its learning, but it does manage to capture the noise present in the training set. The model undergoes multiple epochs of training on insufficient training data due to its restricted size. The model's design consists of many neural layers stacked on top of one another. Because deep neural networks are complicated and take a long time to train, the training set is frequently over-fitted. For address overfitting, there are alternative techniques for reducing model overfitting (69) we used those are Cross-validation, Dropout, Early stopping, and transfer learning. For the proposed study, we applied all above listed techniques for handling model overfitting.

3.10.1 Adding dropout layers.

In a neural network, more weights indicate a more intricate network. One easy way to stop overfitting in a network is to drop nodes in the network probabilistically. Regularization reduces the complexity of the model by arbitrarily ignoring or "dropping out" a certain number of layer outputs.

3.11. Model Evaluation Approaches

When creating and setting up your deep learning models, you have a lot of choices to select. This assessment approach assists in determining which algorithm is most suitable for the presented dataset for a given problem. Similarly, "the best fit" characterizes machine learning, employing the identical input dataset to evaluate the performance of various machine learning models (70). The evaluation method revolves around assessing how effectively the model predicts outcomes.

3.11.1 Accuracy:

It calculates the proportion of all predictions made by the model that are accurate. It serves as a gauge for how well the model categorized the data into the appropriate classifications.

3.11.2 Loss curves:

When comparing various models' performances on the same dataset, loss curves are utilized. Performance is typically better for models with lower, more stable loss curves than for those with higher, more unpredictable curves. Therefore, loss curves can assist us in choosing the model that performs the best for a given task.

3.11.3. Precision

Precision is the proportion of correctly predicted positive observations to all predicted positive observations. It is the ratio of all correct predictions to all positive findings.

$$Precision = \frac{TP}{TP + FP}$$

3.11.4. Recall

The ratio of accurately expected positive observations to all observations made during the actual class is known as recall and it is the proportion of accurate responses that the model generates.

$$Recall = \frac{TP}{TP + FN}$$

3.12 Tools to be used in the Study

During the implementation of our study, we used different types of tools or materials both in hardware and software types listed in below stated table.

3.12.1 Hardware and Software Specification

3.12.1.1 Software Specification

Table 3 Integrated Development Environment Tools

Software & its version	Purpose
Anaconda-navigator	✓ Spyder, Jupyter Notebook, Anaconda Prompt, and other IDEs were installed with it along with Python.
Spyder 5.3.3	✓ It is a Python-based, free and open-source scientific environment created by and for scientists, engineers, and data analysts.
Jupyter notebook 6.5.2	✓ It is utilized in simulations and data visualization. This application is used to manage files, write and execute code, and examine and display data.
Google collaborator (Colab)	✓ A complimentary Jupyter Notebook operates on the cloud, storing information in Google Drive. By enabling users to leverage GPU and TPU, it enables users to run lengthy deep learning code in a short amount of time.

The framework to implement the proposed system

Table 4 Frameworks

Packages	Purpose
NLTK 3.8.1	✓ We have employed data preparation techniques that are pertinent to the development of the proposed system by utilizing this library.
	✓ It is a feature-rich open-source machine learning platform that has a

TensorFlow 2.11.0	strong system in place to manage all aspects of machine learning systems. ✓ We use it when developing deep learning systems for prediction or stage categorization.
Keras 2.12.0	✓ A high-level neural network library is built on top of TensorFlow. These high-level APIs are used to quickly construct and train models since they are more user-friendly because they are integrated into Python.
NumPy 1.24.2	✓ We converted the data into a vector using this software, and then we reshaped it to fit the recommended model.

3.12.1.2 Hardware Specification

Every piece of software and framework covered in the previous section has been installed on a personal computer with the following characteristics.

- ✓ Intel(R) Core (TM) i7
- ✓ 7500U CPU @ 2.70GHz 2.90 GH is the processor.
- ✓ Eight gigabytes of RAM.
- ✓ Hard drive: - 1 TB
- ✓ System: x64-based processor,
- ✓ 64-bit operating system, and
- ✓ Windows: OS, Windows 10 Pro.

CHAPTER FOUR

DESIGNING AND MODEL IMPLEMENTATION

4.1. INTRODUCTION

We provide a thorough explanation of the recommended architectural plan, all of its components, and the methods and instruments used to achieve the study's goals in this chapter. The first section was devoted to clarifying the models' designs. Next, the architecture of the suggested model is explored in the next area, and the implementation flowchart is examined in the third section. Finally, the application of the suggested model was covered in detail in the fourth section.

4.2. The Proposed system Architectures

We divided the model's procedure into two categories in the proposed model architecture: the train process and the categorization phase. There are three stages to the training procedure. Data preparation on the dataset, as we discussed in the technique section, is the first step. Through the extraction of picture features, the second phase converts the cleaned dataset from the first phase into numerical pixel values. The chosen models are trained using those numerical pixel values in the third phase, after which each trained model is saved to a model file.

There are three stages to the classifying procedure as well. In the first phase, we preprocessed the query photos; in the second, we used feature extraction techniques to extract the user's questions; and in the third, we loaded teach trained models and classified the user's query images into the target class using test datasets. Based on a deep learning model, this study has developed an automatic classification method that divides the stages of dental cavity illness into four distinct classifications. The suggested model has the following architecture.

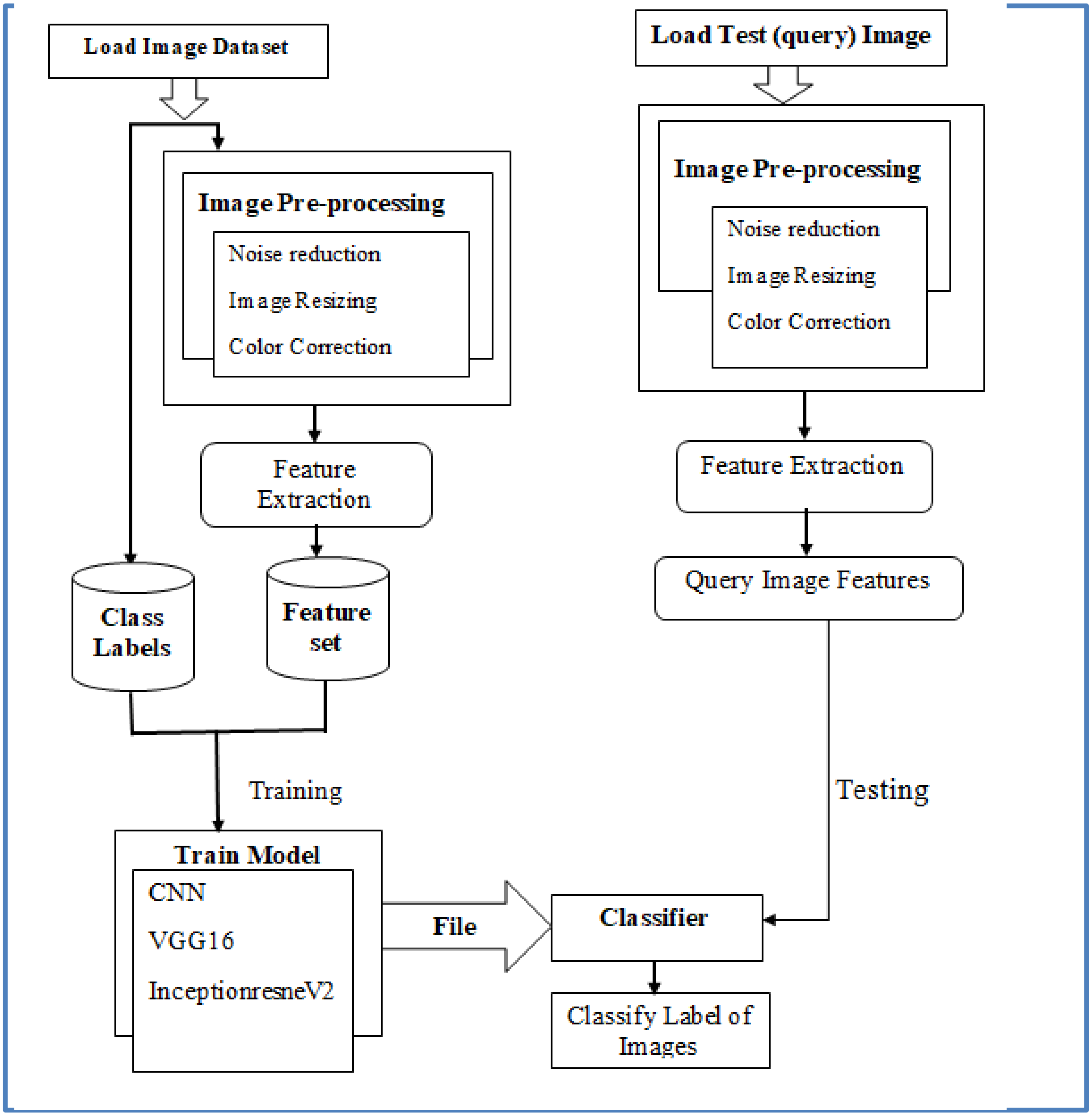

Figure 11 Proposed system Architecture

4.3. System Flowcharts

This section covers the suggested model's implementation, from reading the dataset to the procedure for system evaluation that is also covered below. Reading or loading a dataset, preprocessing it, training and saving the model, loading the saved model, and finally assessing the model are the steps involved in the suggested model implementation.

- ✓ **Loading the datasets: -** Since our dataset was prepared using Image, the first step in reading the files is to import the keras.api library, which has a load () method for reading data.
- ✓ **Preprocessing dataset: -** Preprocessing the dataset is the first step before using it directly. At this phase, the data is cleaned, normalized, augmented, etc.
- ✓ **Train and save model:** - all selected models trained here with the prepared dataset and saved.
- ✓ **Load-trained model: -** the saved model is loaded for prediction purposes with the help of the pickle library.
- ✓ **Evaluate model:** - the loaded model examined here how well it performed.

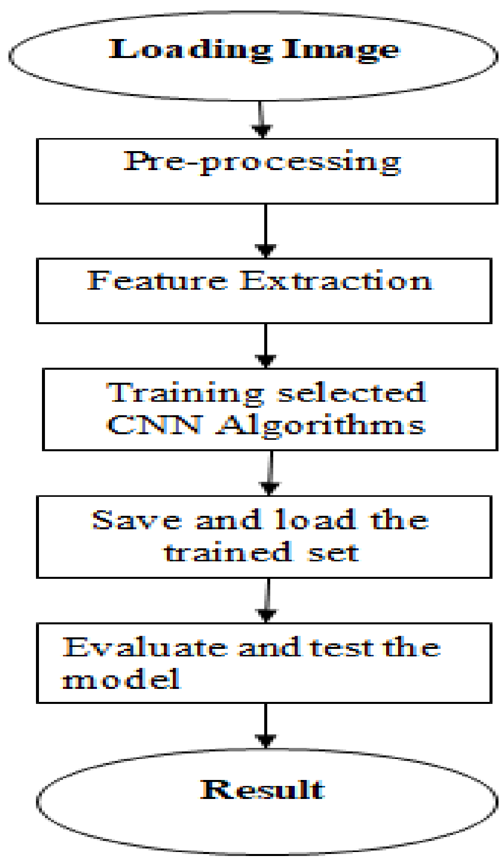

Figure 12 Flowchart of proposed system implementation

4.4 Loading the Datasets

As we discussed in the data preparation section, we employed using tensorflow and Keras API, which is a lightweight data interchange and loading format. By utilizing this all library as shown in the snapshot code below, we read and load our dataset.

```
training_data = '/content/drive/MyDrive/tooth_cavity_class/cavityclassification/train'
testing_data = '/content/drive/MyDrive/tooth_cavity_class/cavityclassification/test'
```

```
#Data agumentation and pre-processing using tensorflow
gen = ImageDataGenerator(
        rescale=1./255.,
        horizontal_flip = True,
        shear_range=0.2,
        zoom_range=0.2,
        vertical_flip=True,
        rotation_range =15,
        width_shift_range = 0.2,
        height_shift_range = 0.2,
        validation_split=0.20) # training: 80% data, validation: 20% data
```

Code 4.1 Snapshot of Data Loading Implementation

4.5. Data Preprocessing Approaches

Data preprocessing aims to facilitate the computer's extraction of the features of image contents and patterns. As we covered in the methodology section, the proposed system was developed using a variety of data preprocessing approaches. In this section, we aim to demonstrate how we put those techniques into practice to create the proposed approach.

4.5.1. Image Resizing

Image resizing to a lesser dimension (224 × 224, 299 x 299), etc.) is frequently used while training vision models in order to facilitate mini-batch learning. Scaling an image is referred to as image resizing.

```
train_datagen = ImageDataGenerator(
        rescale=1./255,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)
```

code 4.2 Snapshot of image resizing implementation

4.5.2. Contrast Enhancement

An essential component of image processing for computer and human vision is contrast augmentation (67). Brightness corrections and grayscale transformations are the two categories of brightness transformations. As seen in the screenshot below, we employed the grayscale methods because

- ✓ **Reduce Dimensions:** Grayscale images are one-dimensional, whereas RGB images include three dimensions and three-color channels.
- ✓ **Cuts down complexity:** Think about using 10x10x3 pixel RGB images to train neural articles. There will be 300 input nodes in the input layer. Moreover, for other algorithms to function: many algorithms are tailored to only function with grayscale images.

```python
#Plot the original image
plt.subplot(1, 2, 1)
plt.title("Original")
plt.imshow(image)

# Adjust the brightness and contrast
# Adjusts the brightness by adding 10 to each pixel value
brightness = 10
# Adjusts the contrast by scaling the pixel values by 2.3
contrast = 2.3
image2 = cv2.addWeighted(image, contrast, np.zeros(image.shape, image.dtype), 0, brightness)

#Save the image
cv2.imwrite('modified_image.jpg', image2)
#Plot the contrast image
plt.subplot(1, 2, 2)
plt.title("Brightness & contrast")
plt.imshow(image2)
plt.show()
```

Code 4.3 Snapshot of Contrast Enhancement Implementation

4.5.3 Normalization

Image normalization makes guarantee that texture instances and data collecting techniques may be compared as best as possible.

```python
# import required library
import cv2

# read the input image in grayscale
img = cv2.imread('/content/drive/MyDrive/colab/dataset2-master/dataset2-master/images/training',0)
print("Image data before Normalize:\n", img)

# Normalize the image
img_normalized = cv2.normalize(img, None, 0, 1.0,
cv2.NORM_MINMAX, dtype=cv2.CV_32F)

# visualize the normalized image
cv2.imshow('Normalized Image', img_normalized)
cv2.waitKey(0)
cv2.destroyAllWindows()
print("Image data after Normalize:\n", img_normalized)
```

Code 4.4.Snapshot of image normalization implementation.

4.6 Image Augmentation Implementation

When a model fails to correctly categorize a picture merely because it was not trained on an image with a different orientation, this is a common issue with image classification models (71). By providing the model with a variety of potential image orientations and transformations during training, this can be avoided. In actuality, though, compiling such a wide range of data could be expensive for a business and take more time, money, and experience. In these situations, generating different images for training by one or more augmentation approaches is a popular method of adding diversity to the current dataset: image data augmentation.

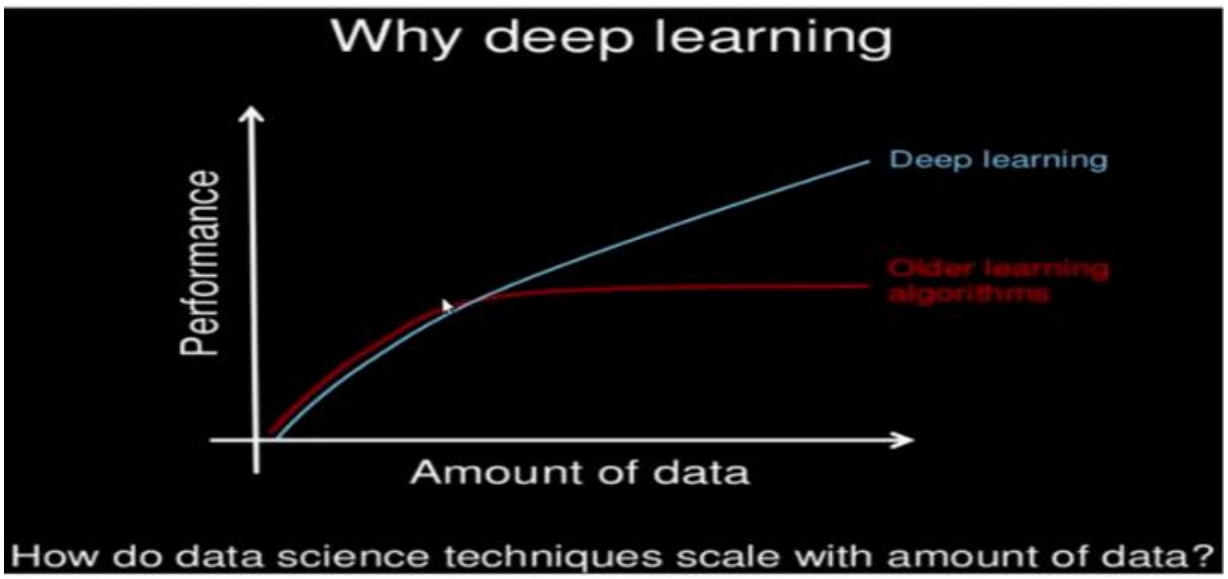

Figure 13 Deep learning Performance and amount of data architecture.

The graph above illustrates how the deep learning model's performance improves with increasing data volume. The issue with insufficient data is that a deep learning model may not be able to identify patterns or functions in the data, which could lead to poor performance. We are unable to obtain a sufficient quantity of pertinent information in the instance of our title. Therefore, we might use image augmentation techniques rather than laboriously gathering the data for days on end. We used a variety of strategies to supplement the image data in this investigation. As demonstrated in the screenshots below, it can involve utilizing geometric transformations to augment image data by flipping, cropping, rotating, zooming, and other operations.

```
import glob from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array, load_img
# Enter Directory of all images
train_dataset = train_datagen.flow_from_directory(
     directory="/content/drive/MyDrive/colab/dataset2-master/dataset2-master/images/training",
datagen = ImageDataGenerator(rotation_range =15),
                         width_shift_range = 0.2,
                         height_shift_range = 0.2,
                         rescale=1./255,
                         shear_range=0.2,
                         zoom_range=0.2,
                         horizontal_flip = True),

data_path = os.path.join(train_dataset,'*g')
files = glob.glob(data_path)
data = []
for f1 in files:
    img = cv2.imread(f1)
    data.append(img)

x = img_to_array(img)
x = x.reshape((1,) + x.shape)

i = 0
path, dirs, files = next(os.walk("folder-name"))
file_count = len(files) #to find number of files in folder

for batch in datagen.flow (x, batch_size=1, save_to_dir =r'new-folder-name',save_prefix="a",save_format='jpg'):
    i+=1
    if i==file_count:
      break
```

Code 4.5 Snapshot of Data Augmentation Implementation

4.7 Model Overfitting Techniques Implementation

4.7.1 Adding dropout (Dropout Layers implementation)

```
# building a linear stack of layers with the sequential model
model = Sequential()

# convolutional layer
model.add(Conv2D(50, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu', input_shape=(32, 32, 3)))

# convolutional layer
model.add(Conv2D(75, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(125, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.25))
# flatten output of conv
model.add(Flatten())
# hidden layer
model.add(Dense(500, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(250, activation='relu'))
model.add(Dropout(0.3))
# output layer
model.add(Dense(10, activation='softmax'))
# compiling the sequential model
model.compile(loss='categorical_crossentropy', metrics=['accuracy'], optimizer='adam')
# training the model for 10 epochs
model.fit(X_train, Y_train, batch_size=128, epochs=25, validation_data=(X_test, Y_test))
```

Code 4.6 Snapshot of Adding dropout layers to selected models.

4.8 Model Implementation

We used the Keras sequential API to apply various deep learning models for the suggested system design. We attempt to demonstrate how each model is implemented in the suggested system in this section.

4.8.1 CNN Model Implementation

```
# Define the CNN model architecture
model = Sequential()
num_channels=3
IMG_WIDTH=224
IMG_HEIGHT=224
# Add the convolutional layer
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(IMG_WIDTH, IMG_HEIGHT,num_channels)))
model.add(MaxPooling2D(pool_size=(2, 2)))

# Add more convolutional layers (optional)
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

# Flatten the 3D feature maps to 1D feature vectors
model.add(Flatten())

# Add the fully connected layers
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))  # Dropout layer for regularization
model.add(Dense(4, activation='softmax'))  # Output layer with softmax activation for multiclass classification
```

```
[18] cnn_model = model
     model.summary()
```

Code 4.7 Snapshot of CNN Model Implementation

4.8.2 VGG-16 Model Implementation

```
#compile the model
from keras import models, layers, optimizers
from keras.layers import Convolution2D, MaxPooling2D, ZeroPadding2D, GlobalAveragePooling2D, AveragePooling2D
import keras.backend as K
import math
from keras.optimizers import SGD,Adam
from keras.applications import VGG16

base_model = VGG16(input_shape=(331, 331, 3), include_top=False, weights='imagenet')

#features = model.predict(x)

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(256, activation='relu')(x)
predictions = Dense(4, activation='softmax')(x)
for layer in base_model.layers:
    layer.trainable = False
model = tf.keras.models.Model(inputs=base_model.input, outputs=predictions)
model = tf.keras.models.Sequential()
model.add(base_model)
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Dense(512, activation='relu'))
model.add(tf.keras.layers.Dense(4, activation='softmax'))
model.compile(optimizer='adam', loss=tf.keras.losses.categorical_crossentropy, metrics=['acc'])
#fit the model
vgg_history = model.fit(train_data_gen,steps_per_epoch=(total_train//batch_size),epochs = 5,
                        validation_data=val_data_gen,validation_steps=(total_validation//batch_size),batch_size = batch_size,verbose = 1)
#model testing
result = model.evaluate(test_data_gen,batch_size=batch_size)
print("test_loss, test accuracy",result)
#save the model file
model_json = model.to_json()
with open("/content/drive/MyDrive/colab/dataset2-master/dataset2-master/images/labels.csv", "w") as json_file:
  json_file.write(model_json)
model.save("/content/drive/MyDrive/colab/dataset2-master/dataset2-master/images/VGG_Classifier.h5")
```

Code 4.8 Snapshot of VGG16 model Implementation

4.8.3 InceptionResNetv2 Model Implementation

```
# load the InceptionResNetV2 architecture with imagenet weights as base
from keras.optimizers import SGD,Adam
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, Flatten, Dense, Dropout
base_model = tf.keras.applications.InceptionResNetV2(
         include_top=False,
         weights='imagenet',
         input_shape=(331,331,3)
         )

base_model.trainable=False
model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.BatchNormalization(renorm=True),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(4, activation='softmax')
  ])
```

Code 4.9 Snapshot of DenseNet121 model Implementation

Based on the above implemented adopted pre-trained models we have contributed our new things on the following points to address our specific tasks:

- ✓ Clearly define the target task or problem we aim to solve using transfer learning and articulating the requirements and objectives of the new task.

- ✓ Choosing an appropriate pre-trained model or architecture based on the characteristics of our target task. Our contribution may involve adapting the architecture to the specific needs of our domain or problem, such as adjusting the number of layers, neurons, or adding task-specific layers.
- ✓ By optimized hyper parameters, including learning rates, batch sizes, and regularization parameter finding a configuration that allows the model to learn effectively from the target data.
- ✓ Defined appropriate evaluation metrics for assessing the model's performance on the target task and interpreting and communicating the results in the context of the specific application.

In general, the new thing in all above implementation code of transfer learning lies in the thoughtful application of pre-trained models that solve specific problems, adapting them to the target domain, and conducting thorough experiments and analyses to understand the effectiveness of the transfer learning approach in our particular context.

CHAPTER FIVE

5. RESULTS AND DISCUSSIONS

The results of the empirical test obtained via data analysis showed and discussed in this section and along with the overall outcomes attained by the model based on quantitative performance indicators and its functionality in real-world settings. We also discussed how the research topics were addressed in this study. After that, the study's ramifications are explored, including how it varies from earlier research on related topics.

5.1 Comparing the selected pre-trained CNN models

The experimental results covered in detail in this chapter. During the experiment, the chosen pre-trained model strategy is used, and the outcomes examined and contrasted. Through dynamic tweaking, the impact of various hyper-parameters on the models' performance examined.

5.2 Parameters Selected on the Pre-Trained Models

The pre-trained models that have been chosen have their parameters adjusted to make them appropriate for use as a pose and compatible with local data. The parameters that were employed in this study to fine-tune each of the three pre-trained CNN models that were chosen are shown in the table below.

Table 5: Hyper-parameter tuning values

Selected Pre-trained models	**Applied Hyper-parameters**	**values**
CNN **InceptionResNetV2** **VGG-16**	Batch-size	[32,64,128]
	Optimizers	[Adam]
	Learning-rate	[0.001]
	dropout	[0.25-0.5]
	Activation function	[ReLU, Softmax]
	Loss	CategoricalCrossentropy
	Epochs	[10]

In our study we used only number of epochs for iteration only with 10 epochs, because of:

- ✓ Limitation of computational resource we have. Training deep learning models can be computationally expensive, especially with large datasets and complex architectures. In such cases, we used a smaller number of epochs due to constraints on computational resources.
- ✓ In our study we used transfer learning with a pre-trained model, so that fewer epochs might be sufficient to adapt the model to the new task.
- ✓ Our dataset is small, the model might be prone to over fitting if trained for too many epochs. Limiting the number of epochs helps prevent over fitting on limited training data.

However, it's important to note that the optimal number of epochs can vary widely across different tasks and datasets. It is common practice to monitor the model's performance on a separate validation set during training and adjust the number of epochs accordingly.

5.3. Model Training, Testing and Evaluation

The process of evaluating a model involves using metrics to analyse the model's performance. We demonstrated each model hyper parameter setting and the accuracy they attained using the model we created in the previous chapter. We can show the outcomes after the model has been assessed. The model's learning behaviour during training and the model's performance estimation are the two main components that need to be presented. Making a line plot to display the model's results based on the training with validation sets during training is the first step in the diagnostics process. These charts are useful for determining if a model achieves the dataset well or if it is overfitting or under fitting.

Two figures, one for training loss and the other for validation loss, both have two subplots. The blue lines will show model loss on train data, and model validation during training on the holdout validation dataset will be shown by the orange lines. When the model is trained on both training and validation datasets, the training loss and validation loss are displayed in the second subplot. The orange lines represent the model's validation loss during training on the holdout validation dataset, and the blue lines represent training loss on the training dataset. As a result, the full model that we trained in the previous chapter is shown below based on their outcome.

5.3.1. CNN model evaluation result

We trained and assessed our CNN model architecture for multiclass image classification based on our dataset collection and classes. After experimenting with various parameters, we found that learning rate 0.001 and batch size 128 yield higher results on both training and validation accuracy. In our investigation, the CNN model attains 89.99% and 91.10% training accuracy based on the hyper parameter configuration shown in Table 5.1 above. We reported that CNN models yielded training accuracy of 0.899% and validation accuracy of 0.9110% in the table below.

Table 6 The CNN accuracy result

No	CNN training accuracy result (%)	The CNN validation accuracy result (%)
1	0.899%	0.9110%

After training our CNN model with different parameters, the training and validation accuracy curve, and loss value curve we got are stated below respectively.

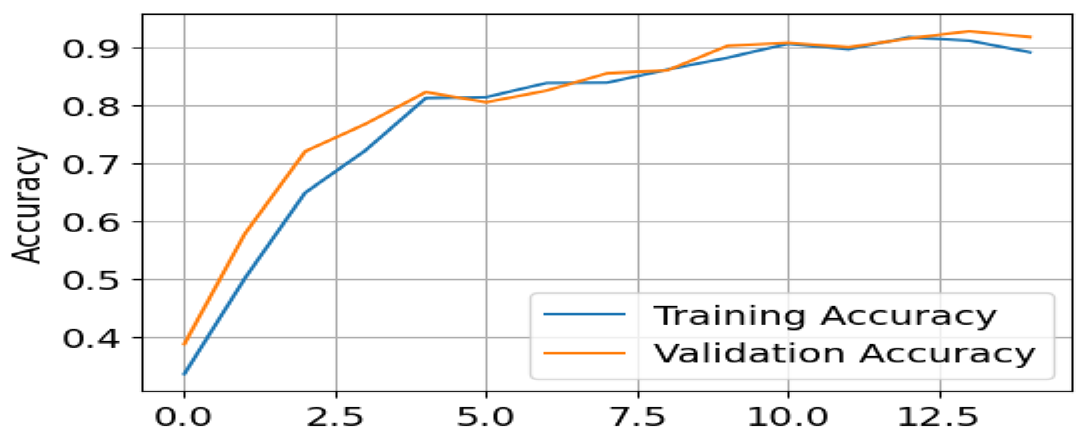

Figure 14 Accuracy value curve of CNN model

The lower the loss values the best the model is. Here in table 5.3 CNN achieved a train loss 0.2894% and validation loss 0.2742%.

Table 7 The CNN loss value result

No	CNN training loss result (%)	The CNN validation loss value result (%)
1	0.2894%	0.2742%

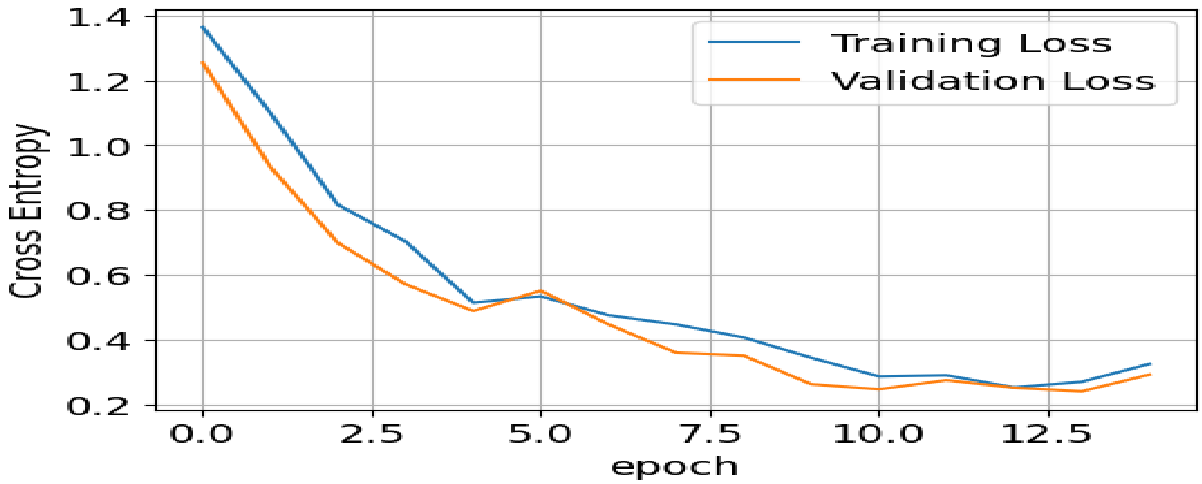

Figure 15 loss value curve of CNN model

5.3.2. InceptionResNetV2 model Implementation result

Based on the hyper-parameter combination shown in first Table 5.1 above, the InceptionResNetV2 model achieved an accuracy of 97.77%.

Table 8 InceptionResNetV2 accuracy result

No	InceptionResNetV2 training accuracy result (%)	InceptionResNetV2validation accuracy result (%)
1	**0.977%**	**0.978%**

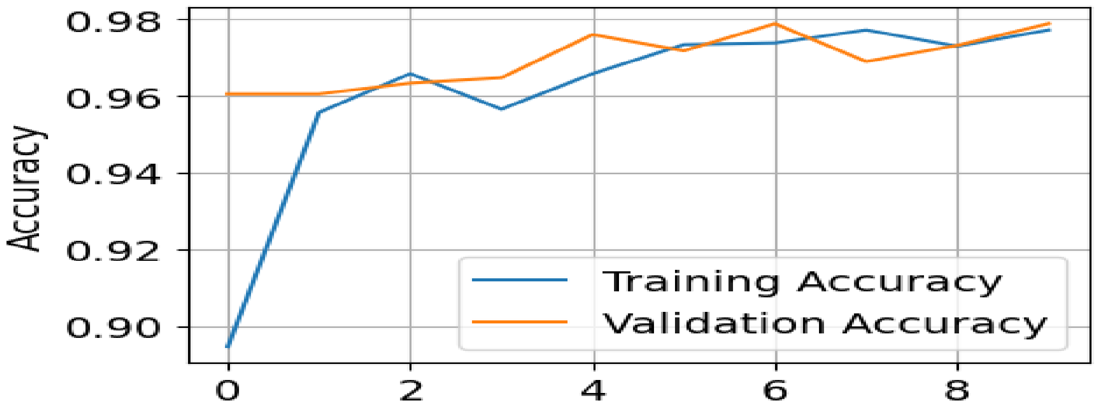

Figure 16 accuracy curve of InceptionResNetV2 model.

In below table also illustrates the training and validation loss values of InceptionResNetV2 during the training.

Table 9 InceptionResNetV2 loss value

No	InceptionResNetV2 train loss curve result (%)	InceptionResNetV2 validation loss curve result (%)
1	0.0883%	0.0653%

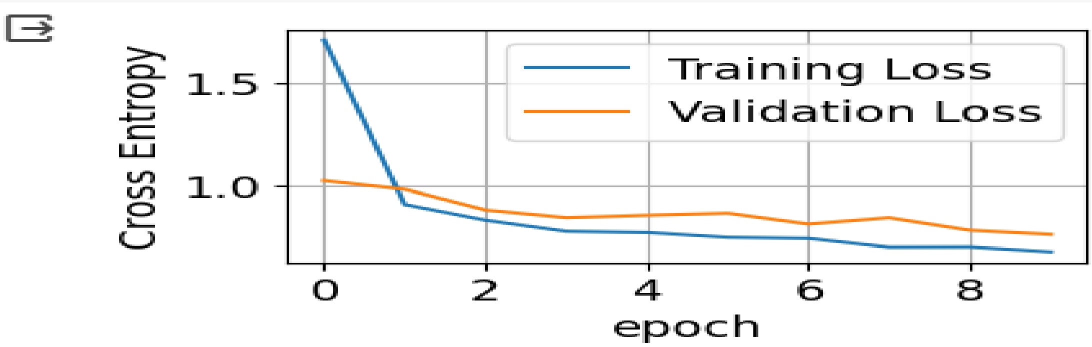

Figure 17.Loss curve value of the InceptionResNetV2 model.

5.3.3. VGG-16 model Implementation result

At 92.43% accuracy, the VGG-16 model achieved the hyper-parameter configuration shown in Table 5.1 above.

Table 10 VGG-16 accuracy result.

No	VGG-16 training accuracy result (%)	VGG-16 validation accuracy result (%)
1	**0.9243%**	**0.9557%**

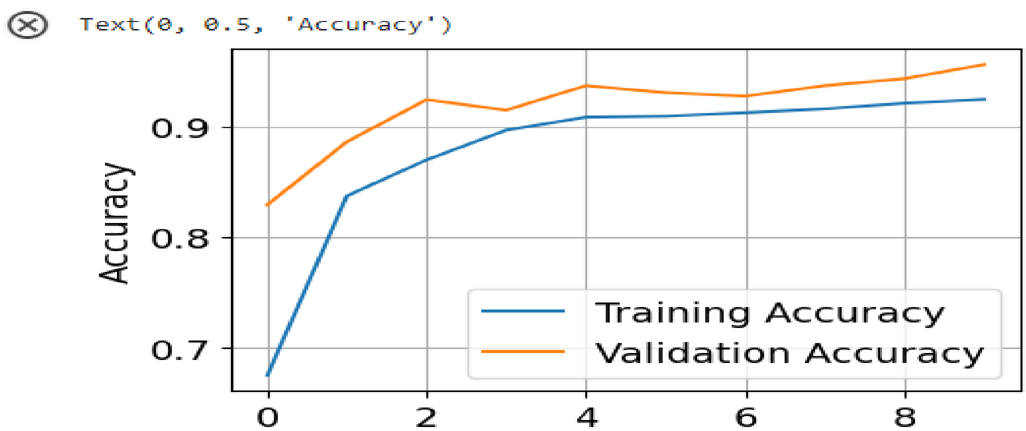

Figure 18 accuracy curve value of the VGG-16 model.

Table 11 : VGG-16 loss curve result.

No	VGG-16 train loss result (%)	VGG-16 validation loss result (%)
1	**0.1791%**	**0.1322%**

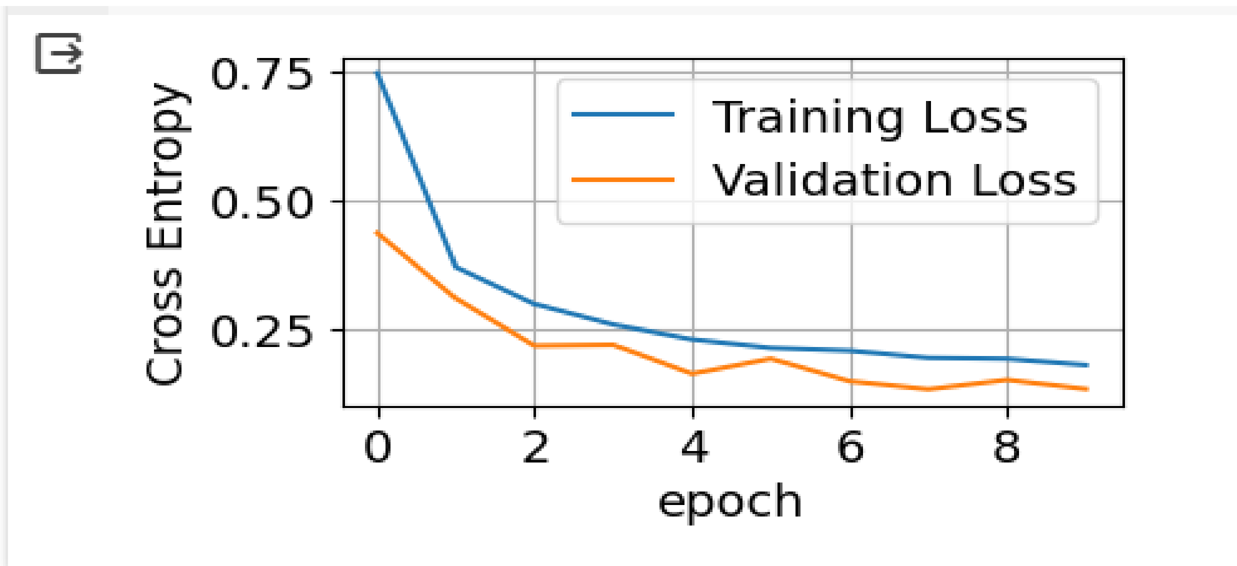

Figure 19 loss value curve of the VGG-16 model

5.4 Comparisons between Testing and Fine-tuned Models

In our research work, we tried to compare three CNN architectures and select the best model art to classify stages of dental caries diseases after we made different comparative analyses based on different evaluation metrics. Based on this we compared pre-trained VGG-16, pre-trained InceptinResNetV2, and CNN deep neural networks. As stated in the table below InceptinResNetV2 and VGG-16 archived remarkable results on both training and testing datasets than CNN model. 89.99% training accuracy and 91.10% validation accuracy were attained by CNN.

Moreover, Vgg-16 demonstrated exceptional accuracy on training and testing datasets. Pre-trained Vgg-16 produced a Training accuracy of 92.43% and a Validation accuracy of 95.57%, as is more clearly indicated in Table 5.6 above. This accuracy result is almost the same as what CNN models produce. Despite this, InceptionResNetV2 and VGG-16 both produced excellent results on the training and testing datasets. Comparing the three top-performing models in terms of additional evaluation criteria, such as precision-recall F1-score, still shows that InceptionResNetV2 is different, as the table below illustrates.

Table 12: Training, Validation, and Testing Accuracy Models

Models	Training Accuracy	Validation Accuracy	Testing Accuracy
CNN models	89.99%	91.10%	84.22%
VGG-16	92.43%	95.57%	92.11%
InceptionResNetV2	97.77%	97.78%	97.50%

The all above explanations answer our first research question, which that answered after comparing different CNN architectures using the same number of datasets for all compared CNN architectures. From our experiment, InceptionResNetV2 is the best CNN architecture in this scenario. Even though the optimal hyper-parameter is different, from architecture to architecture in case, we applied dropout on all models and it yields the best accuracy during training. Learning rates of 0.001 and 0.01 also became optimal in most cases.

To put it simply, the Loss function is a way to gauge how effectively your algorithm models the data that you have provided. It is a mathematical function of the machine-learning algorithm's parameters. From this point of view, InceptionResNetV2 achieved the best training loss with 0.0883 and 0.0653 validation losses. Even though VGG-16 has a good loss on training loss but it’s not as good on training and validation accuracy. InceptionResNetV2 has an overall good loss on both training and validation loss. This makes InceptionResNetV2 a good model when compared to others.

***Table 13* Training and validation loss value of Models.**

No	Selected Models	Training loss value (%)	Validation Loss value (%)
1	CNN	0.2894%	0.2742%
2	InceptionResNetV2	0.0883%	0.0653%
3	VGG-16	0.1791%	0.1322%

5.5. Model Testing and Classification Report

This section describes the classification report that we used confusion matrix to measure the models using the test data set. We did this by counting the amount of test samples that our best model, which is shown, correctly and incorrectly classified in each class (category). The confusion matrix presented below indicates how ResNetV2 categorized the 200 test dataset images based on labels at the time of conception. There are four classes in the test dataset, and there are fifty photos in each class.

- ✓ **In Class 1:** (Dentin Decay), from **50** image datasets, **48** images labeled to their class.
- ✓ **In class 2:** (Enamel Decay), from **50** image datasets, **50** images are labeled correctly.
- ✓ **In class 3:** (Healthy), from **50** images **47** images classified correctly labeled.
- ✓ **In class 4**: (Pulp Decay) from **50** image datasets, **50** images labeled to their class.

In general, following a comparison of the top model using the assessment criteria (training accuracy, validation accuracy, precision, recall, and F1 score) described above, InceptionResNetV2 records the remarkable score from those two models. Therefore, according to the classification report by inceptionResNetV2, from the 200 test image datasets, 195 images are correctly classified to their labels and 5 images are miss classified.

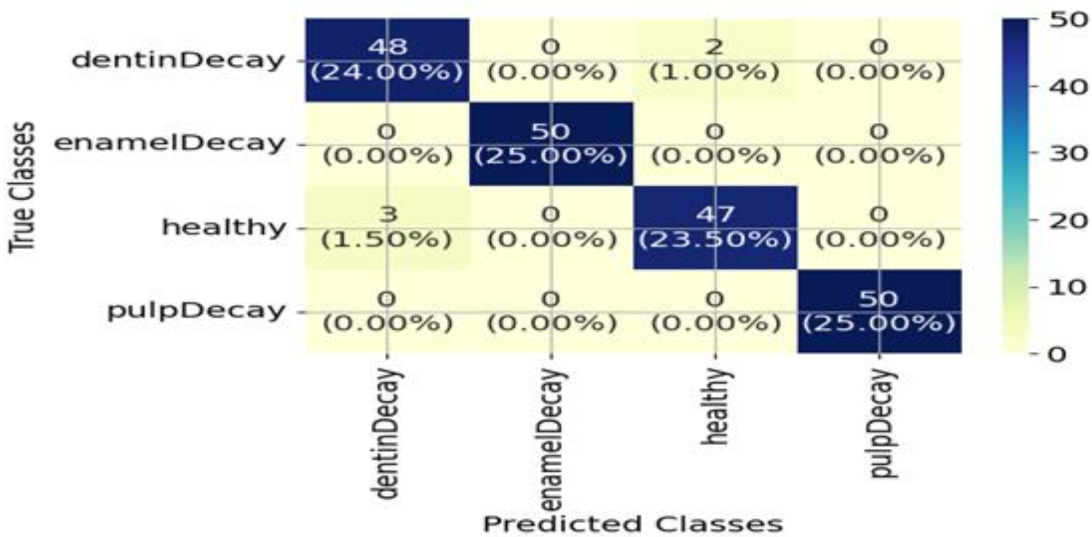

Figure 20 Classification report for InceptionResNetV2 model

5.6 Model Evaluation Metrics

Fitting and assessing the model is necessary after it has been defined and trained. The batch size and number of training epochs must be supplied to fit the model. We employed a small batch size of 64–128 and a generic 20 training epochs in our investigation. We divided the training dataset into train, test, and validation sets to improve accuracy and performance. The aforementioned conclusions were all drawn from the model's performance data.

```
#fitting the model
History=model.fit(train_generator, epochs=10, batch_size=64,verbose=1,
                  validation_data=validation_generator, callbacks=[early))
```

Once the model is fit, we can evaluate it directly on the test dataset.

```
#to evaluate the model
-,acc=model.evaluate(test_generator)
```

Code 5.1 Snapshot for evaluating model with test datasets

However, since accuracy only becomes a reliable indicator of a model's performance when it is trained on balanced datasets; there are no balanced classes to use in this evaluation. In short, accuracy quantifies the extent to which a model has been trained using the input data. As a result, all trained models are evaluated using additional metrics like F measure, precision, and recall. Micro and macro averages, along with weighted averages for each metric (precision, recall, and F1 score), were employed in our investigation.

- ✓ First, according to the model CNN we achieved the overall accuracy of 92.61 training accuracy and 87.1% validation accuracy, for cavity stage classification, CNN showed Recall result of DD/ED/PD/H classification were **0.865%, 0.892%, 0.886% and 0.918%**, respectively.
- ✓ The second model VGG16 achieves an overall accuracy of 0.942% and 0.926% in both training and validation, when we come to evaluate the classification result of VGG16; it scored the Recall value of DD/ED/PD/H of **0.915%, 0.938%, 0.897% and 0.940%** respectively.

✓ In the third model InceptionResNetV2 we, get the overall accuracy of **0.977%** and **0.9778** training and validation accuracy and recall of **0.96%, 1.00%, 0.94%, and 1.00%** respectively. The InceptionResNetV2 was scored a novel accuracy higher than VGG16 and CNN models in classification tasks. The recall, precision and F1-score result of this model was stated in the figure below.

	precision	recall	f1-score	support
dentinDecay	0.94	0.96	0.95	50
enamelDecay	1.00	1.00	1.00	50
healthy	0.96	0.94	0.95	50
pulpDecay	1.00	1.00	1.00	50
accuracy			0.97	200
macro avg	0.98	0.97	0.97	200
weighted avg	0.98	0.97	0.97	200

Figure 5.7 Evaluation Metrics for InceptionResNetV2

After we compared the three selected pre-trained model by using different parameters in table 5.8 and 5.9, we conclude InceptionResNetV2 is the best algorithm from the three selected. The all above explanations clearer answer from our experiment, InceptionResNetV2 is the best CNN architecture in this scenario.

5.6 Model testing

As was covered in the item above, there are two stages to the image classification process: the training phase and the testing phase. To classify the photos according on the expected labels, the customized deep pre-trained CNN receives all of the dataset images during the training phase. The testing set, which is made up of a collection of testing samples, should be kept apart from the training and validation sets throughout the testing phase, but it should still have the same probability distribution as the training set. There are 456 photos in our test dataset, divided into four distinct categories. Finally, we used these test datasets that had not yet been seen to evaluate and test our chosen model, predicting the true labels (anticipated outcomes).

5.7 Model predictions

The pre-trained CNN architecture mentioned above was compared, and the best model was chosen and preserved. The newly created clinical images (test dataset) are fed into the model that has been saved. Ultimately, the outcome examined by show casing the many phases of the tooth cavity type. More efficient and fine-tuned models manage this prediction.

5.8 Comparison with Related Research Work

The many, studies conducted on illnesses of the tooth cavity. Nobody has, however, put the deep learning algorithms for tooth cavity phases into practice. Our research centered on categorizing dental cavity phases by contrasting previously taught CNN systems. While conducting our research, we compared the accuracy of our model to that of current (particularly 2019–present) papers; however, the goals of our work differ from those listed in the table below, indicating that not all related papers are centered on cavity stage classification; rather, some of them are based on lesion classifications and other oral health issues. The articles presented in the table below have varied goals when it comes to the classification of dental cavity phases. Nevertheless, when their goals diverge.

Table 14 Summary of related recent research work

<table>
<tr><th>No</th><th>Authors</th><th>methodology</th><th>Objectives</th><th>The accuracy they achieved.</th><th>Accuracy Achieved by our Model.</th></tr>
<tr><td>1</td><td>Haihua Zhu1 Zheng Cao2 et.al</td><td>CariesNet as a U-shape network.</td><td>Segmentation of multi-stage caries lesions.</td><td>93.61% overall accuracy</td><td rowspan="2">97.7% for the classifying of four different stages of caries.</td></tr>
<tr><td>2</td><td>Faruk Oztekin, and et.al</td><td>ResNet-50 EfficientNet-B0 and DenseNet-121</td><td>Classify dental X-ray images into cries or non caries.</td><td>Performance with a rate that reaches 92.00%</td></tr>
</table>

5.9 Graphical User Interface for determining the stages of tooth cavity disease.

Designing a Graphical User Interface (GUI) for determining the stages of tooth cavity disease involves creating a user-friendly application that allows users, such as dentists or healthcare professionals, to input relevant data and receive information about the stage of tooth cavity. After we developed the system, we implemented GUI to enhance the system key components and considerations such as:

- ✓ **Visual Data:** Allow the user to input visual data, such as images or X-rays of the patient's teeth.
- ✓ **Image Viewer:** Provide a section for viewing dental images or X-rays. This could include a zoom-in and zoom-out feature for detailed examination.
- ✓ **Algorithm Integration:** Implement algorithms or models that can analyze the input data and determine the stage of tooth cavity disease. This may involve image processing techniques for analyzing dental images.
- ✓ **Explanation:** Include an informative section explaining the characteristics of each stage, helping users understand the analyzed results.

Figure 5.8 determining of tooth cavity stages using GUI

5.10. Discussion

As we discussed in section 1.6.1, the objective of this study was to investigate a CNN pre-tarained model for determining the stages of tooth cavity disease. In addition to achieving this objective, this research was provided to answer the research question listed in section 1.5 To answer those questions, we used different techniques. Let us see the techniques that have been applied to answer the research questions and how the proposed system answered those questions one by one.

The first research question of this study is, "how effective are deep learning techniques, specifically a pre-trained Convolutional neural network (CNN), in the accurate predictions of tooth cavity stages using dental X-ray images?". We answered this question, by selected a CNN pre-trained neural network model which is trained on huge amounts of data and we adopted with our task which is based on identifying the stages of tooth cavity diseases and we compared their performance with different metrics.

The second question of this study is "what is the performance comparison between the implemented CNN model and expert dentists in determining different stages of tooth cavity diseases?" Generally we answered this question by implementing the pre-trained CNN model and train our collected datasets. After we train and validate our model we evaluated the selected system performance and dentist experts by applying the evaluation metrics such as precision, recall and F1 score. Therefore from our model experiments, the InceptionResNetV2 becomes the same and high prediction accuracy when we compared to the dentist accuracy.

The last and third question of this study is "To what extent do pre-trained models, contribute to the improvement of classification accuracy for tooth cavity diseases compared to a non-pre-trained model?" We addressed this question by comparing the basic CNN non pre-trained algorithm and pre-trained model algorithm during our experiments. In case of our dataset limitation we used transfer learning techniques which are described under the 3.5 section. In our study we use this technique that is called pre-trained CNN models (VGG 16 and InceptionResNetV2") models which layers are trained on huge amounts of datasets previously. Therefore, from these models InceptionResNetV2 achieved a high accuracy both in training, validation and test datasets. However, pre-trained model perform more than non-pre-trained model with predictions the class of tooth cavity stages.

CHAPTER SIX

6. CONCLUSION, RECOMMENDATION AND FUTURE WORK

This chapter provides an overview of our work, delving into the conclusion, recommendations, and potential future developments. We also elucidate the comprehensive steps undertaken in the completion of this study, highlighting our findings, suggestions, and ways to enhance future endeavours.

6.1. Conclusion

This research described a method for detecting stages of tooth cavity using dental image radiography (X-ray), along with the phases of the dental cavity classification methodology. In order to attain the intended outcomes, pictures were gathered from various hospitals and dental clinic offices. This allowed for the presentation of four distinct classes that represented the various stages of tooth caries. The labeled data underwent pre-processing, various augmentation operations, and normalization as mandated by our model. Before training, the enhanced and normalized picture datasets were divided into test, validation, and training datasets. To support the medical staff in the diagnostic process, each tooth or group of teeth is numbered and, depending on the case, a report is prepared detailing the problems of dental caries for each case.

The goal of this work is to categorize dental X-ray cavity pictures according to the stages of the cavity. Using this data, two pre-trained models and one standard CNN model are trained, producing varying noteworthy accuracy points. The implemented method was compared to similar algorithms and assessed using a variety of criteria. We choose InceptionResNetV2, the model with the highest accuracy for this investigation, after evaluating our generated models. Ultimately, the study produced encouraging findings, but more research is required.

6.2 Recommendation

In order to detect and categorize tooth cavity stage picture data, we have looked at a number of research-oriented concepts based on building a deep neural network model in this work. When compared to other medical datasets, the dental department's medical image collection is somewhat small. We obtained the datasets from the Waliin dental clinic in Jimma town, a specialized referral hospital of Jimma University, were used to create the suggested model. Even if the suggested effort produced a satisfactory result, more data collection should be done in order to expand the dataset and enhance the model's capacity for generalization. As a result, it suggested gathering further datasets.

Furthermore, the study was restricted to detecting dental cavity illnesses in just four stages. It is crucial for dental treatment to incorporate additional cavity situations, such as abscesses and demineralized cavity stages, which are not covered in our work. To further improve performance, we suggest creating an ensemble model, a model for disease diagnosis based on images, and a knowledge base system for diagnosing dental caries stages based on patient data or other input.

6.3 Contribution

To the best of our abilities, this study worked the following during our research work to get high accuracy model performance to effectively determine cavity stages:

Technical Contribution: we have investigated and researched 4-tooth cavity classifying their stages based upon pre-trained models. Based on the gap from previous work, this analysis achieved high accuracy model performance and was done on larger image datasets.

Dataset: during the investigation, we collected 4275 tooth cavity disease images from Jimma University specialized hospital and Waliin medium Dental clinic in Jimma town.

Scientific Contribution: as a scientific contribution, there was no previous research that is based on determining the stages of tooth cavity diseases.

6.3 Future Works

The purpose of this work was to design and investigate deep-learning methods for the classification of dental cavity phases. This study used a few deep-learning pre-processing techniques to accomplish the goals. However, because they require more time and work, not all types of deep learning approaches, models, and evaluation criteria are completed in this paper work.

All those models and methodologies will be available for the researchers to use in the future to put into practice a more effective system. Furthermore, this study concentrates on only three types of dental cavity stages (caries tooth) and with healthy tooth (non-caries) generally four classes, due to a lack of reliable datasets and data imbalances. Therefore, the researchers may address this by gathering all the necessary datasets on the demineralized and abscess stages of the cavity, resulting in a more thorough study that will benefit everyone.

Reference

1. *Deep learning convolutional neural network algorithms for the early detection and diagnosis of dental caries on periapical radiographs.* Nabilla Musri, 1 Brenda Christie,1 Solachuddin Jauhari Arief Ichwan,2 and Arief Cahyantocorresponding author3,4,5. 2021 Jul 13.

2. *The global burden of oral diseases and risks to oral health.* Poul Erik Petersen, 1. 7 July 2005.

3. *An Explainable Deep Learning Model to Prediction Dental.* 1, Faruk Oztekin. 7 January 2023.

4. *CariesNet: a deep learning approach for segmentation of multi-stage.* Haihua Zhu1 • Zheng Cao2 • Luya Lian1 • Guanchen Ye1 • Honghao Gao3, 4 • Jian Wu5. 7 January 2022.

5. *A Deep Learning-Based Approach for the Detection of.* 1, Dima M. Alalharith. 15 November 2020.

6. *A Deep Learning Approach for Automated Diagnosis and Multi-Class.* Farheen Ramzan1 & Muhammad Usman Ghani Khan1 & Asim Rehmat1 & Sajid Iqbal1, 2 & Tanzila Saba3 & Amjad Rehman4 &. 18 December 2019.

7. *New 2D Matrix-Based Neural Network for.* M. Mohamadian, H. Afarideh and F. Babapour. revised March 11, 2015.

8. *A deep learning model using convolutional neural networks for* . Xiaoyi Zang1, 2#^, Chunlong Luo3,4#, Bo Qiao1,2, Nenghao Jin1,2, Yi Zhao3*, Haizhong Zhang2*^. Dec 19, 2022.

9. *he Oral Microbiome in Dental Caries.* STRUŻYCKA, IZABELA. 1 February 2014.

10. *Integrated Predictive Analysis for Periodontal.* Naresh Kumar M, Lakshmi TK,DILLI BABU SLAVAKKAM,Ramesh Babu Ch,Rajendra Pamula. August 25th, 2023.

11. *Dental Enamel Formation and Its Impact on.* James P. Simmer, D.D.S., Ph.D. and Jan C-C. Hu, B.D.S., Ph.D. 7/23/01.

12. *Prevalence and Severity of Oral Diseases in the Africa and Middle East Region.* A. Abid, F. Maatouk, L. Berrezouga, C. Azodo, O. Uti, H. El-Shamy, and A. Oginni. June 22, 2015.

13. *Dental Caries and Associated Factors Among.* Amare Teshome, Getaneh Andualem & Kirubel Derese. 11 Nov 2022.

14. *Prevalence of Dental Caries and Its Associated Factors among.* Anguach Shitie, A. 15 March 2021.

15. *Dental caries and associated factors in.* Tesfu Zewdu1*, Duresa Abu2. 2021.

16. *A Survey on Deep Learning in Medical Image Analysis.* Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi,. 4 Jun 2017.

17. *Deep Feature Extraction and Classification of.* Yushi Chen, Member, IEEE, Hanlu Jiang, Chunyang Li, Xiuping Jia, Senior Member, IEEE, and.

18. *Detection Activity.* Mariana M. Braga, DDS, PhDa. 2010 .

19. *Generalizability of Deep Learning Models for Caries Detection.* Agnes Holtkamp 1, 2, Karim Elhennawy 3. 1 March 2021.

20. *deep learning approach for segmentation of multi-stage.* Haihua Zhu1 • Zheng Cao2 • Luya Lian1 • Guanchen Ye1 • Honghao Gao3, 4 • Jian Wu5. 27 October 2021.

21. *Deep Learning for Caries Detection and Classification.* Luya Lian, Tianer Zhu, Fudong Zhu * and Haihua Zhu *. 13 September 2021.

22. *Dental Caries Detection Using Score-Based.* 1, ANDAC IMAK. February 9, 2022.

23. *A deep learning model using convolutional neural networks for .* Xiaoyi Zang1, 2#^, Chunlong Luo3,4#, Bo Qiao1,2, Nenghao Jin1,2, Yi Zhao3*, Haizhong Zhang2*^. Dec 19, 2022.

24. *A Deep Learning-Based Approach for the Detection of.* 1, Dima M. Alalharith. 15 November 2020.

25. *Binary cross entropy with deep learning technique for Image classification.* Yendapalli, Vamsidhar. October 2020.

26. *A study on Image Classification based on Deep Learning and.* Abu1, Mohd Azlan. 2017.

27. *Binary cross entropy with deep learning technique for.* Ruby1, Dr.A.Usha. July – August 2020,.

28. *Deep Decision Network for Multi-Class Image Classification.* Murthy∗1, Venkatesh N.

29. *Learning Spatial Regularization with Image-level Supervisions.* Feng Zhu1, 2.

30. *Deep Learning for Hierarchical Severity Staging of.* Nikan K. Namiri, BS • Io Flament, MS • Bruno Astuto, PhD • Rutwik Shah, MD • Radhika Tibrewala, MS •. January 10, 2020.

31. *A review of the application of deep learning in medical image classification and segmentation.* Lei Cai, 1 Jingyang Gao,corresponding author 1 and Di Zhaocorresponding author 2.

32. *AI applications to medical images: From machine learning to deep learning.* Isabella Castiglioni a, b,1. 13 February 2021 .

33. *A survey of deep learning techniques for autonomous driving.* Macesanu, Sorin Grigorescu | Bogdan Trasnea | Tiberiu Cocias | Gigel.

34. *Deep Learning applications in agriculture: a short review.* Lu´ıs Santos1, 2.

35. *Lu´ıs Santos1,2.* Alexander Warnecke∗, Daniel Arp∗, Christian Wressnegger† and Konrad Rieck∗. 2020.

36. *Deep Learning for Social Media Analysis in Crises Situations.* Granmo, Mehdi Ben Lazreg Morten Goodwin Ole-Christoffer. June 2016.

37. *Advancements in Dentistry with Artificial Intelligence: Current.* 1, Anum Fatima. October 2022.

38. *Dental cavity Classification of using Convolutional.* Sonavane1, Apurva. 2021.

39. *Caries detection with tooth surface* . Eun Young Park1†, Hyeonrae Cho2,3†, Sohee Kang1. 2022.

40. *The Caries Process and Its Effect on the Pulp: The Science.* Lars Bjørndal, DDS, PhD. 2008.

41. *Deep Learning Application in Dental Caries Detection Using.* Mai Thi Giang Thanh 1, 2, Ngo Van Toan 3,4, Vo Truong Nhu Ngoc 2. 29 May 2022.

42. *Teeth Detection and Dental Problem Classification in* . Mircea Paul Muresan, Andrei Răzvan Barbura, Sergiu Nedevschi. 2020.

43. *Review of Deep Convolution Neural Network in* . Ahmed Ali Mohammed Al-Saffar, Hai Tao, Mohammed Ahmed Talab. 2017.

44. *Automated caries detection* . Duc Long Duong, Malitha Humayun Kabir, Rong Fu Kuo. 2021.

45. *Deep Learning Application in Dental Caries Detection Using.* Mai Thi Giang Thanh 1, 2, Ngo Van Toan 3,4, Vo Truong Nhu Ngoc 2.

46. *Some Improvements on Deep Convolutional.* Howard, Andrew G.

47. *Deep Convolutional Neural Networks for Image.* Waseem Rawat, Zenghui Wang.

48. *Deep convolution neural network for image recognition.* Boukaye Boubacar Traoré, Bernard Kamsu-Foguem, Fana Tangara. 2018.

49. *Deep Residual Learning in Spiking Neural Networks.* Wei Fang1, 2. 2021.

50. *K. Zhang, Y. Guo, X. Wang, J. Yuan, and Q. Ding, ―Multiple feature reweight DenseNet* . KE ZHANG, (Member, IEEE), YURONG GUO, XINSHENG WANG,. 29, 2019., Vols. VOLUME 7, 2019.

51. *Pre-trained VGGNet Architecture for.* Usman Muhammad and Weiqiang Wang, Shahbaz Pervaiz Chattha,Sajid Ali.

52. *Optimization of Image Embeddings for Few Shot.* Arvind Srinivasan, Aprameya Bharadwaj,Manasa Sathyan,S Natarajan.

53. *Dental caries and associated factors among.* Geleto1, Aliye.

54. *Prevalence of timely complementary feeding.* AbateID1, Moges Wubneh.

55. *An Explainable Deep Learning Model to Prediction Dental.* 1, Faruk Oztekin. : May 18, 2022.

56. *Caries detection with tooth surface* . Eun Young Park1†, Hyeonrae Cho2,3†, Sohee Kang1. 2022.

57. *CariesNet: a deep learning approach for segmentation of multi-stage.* Haihua Zhu1 • Zheng Cao2 • Luya Lian1 • Guanchen Ye1 • Honghao Gao3, 4 • Jian Wu5. 7 January 2022.

58. *Automatic Feature Segmentation in Dental Periapical Radiographs.* 1, Tugba Ari. 7 December 2022.

59. Fuzhen Zhuang, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Senior Member, IEEE,. *A Comprehensive Survey on Transfer Learning.*

60. *PRACTICAL METHODS OF IMAGE DATA PREPROCESSING.* Shin1, Yunjung. 2020.

61. *Comparison of Image Normalization Methods for Multi-Site.* Steffen Albert 1, * , Barbara D. Wichtmann 2.

62. *Contrast Enhancement of Fundus Images by.* 1, KHURSHEED AURANGZEB.

63. *Impact of Image Resizing on Deep Learning Detectors.* Saponara1, Sergio.

64. *A Survey of Feature Selection and Feature.* Samina Khalid, Tehmina Khalil,Shamila Nasreen.

65. *Scalable Marginal Likelihood Estimation for Model Selection in Deep Learning.* 5, Alexander Immer 1 2 Matthias Bauer † 3 4 Vincent Fortuin 1 Gunnar Rätsch 1 2 Mohammad Emtiyaz Khan.

66. *VGG-16 (Visual Geometry Group).* Mu Ye, Ni Ruiwen, Zhang Chang, Gong He, Hu Tianli, Li Shijun, Sun Yu, Zhang Tong, and Guo Ying.

67. *Deep Koalarization: Image Colorization using.* Federico Baldassarre∗∗, Diego Gonz´alez Mor´ın∗∗, Lucas Rod´es-Guirao??

68. *Hyper parameters selection for image classification in convolutional neural networks.* Nazir, Sajid, Patel, Shushma and Patel, Dilip.

69. *Analyzing Overfitting under Class Imbalance in.* Zeju Li, Konstantinos Kamnitsas and Ben Glocker.

70. *Evaluation of Deep Learning Models for Identifying Surgical Actions.* Shuja Khalid, MSc, et al.

71. *Data augmentation for improving deep learning.* Agnieszka Mikołajczyk, Michał Grochowski.

72. *Deep learning convolutional neural network algorithms for the early detection and.* Nabilla Musri 1, Brenda Christie 1, Solachuddin Jauhari Arief Ichwan 2, Arief Cahyanto. 2021.

73. *A deep learning model using convolutional neural networks for caries detection and recognition with endoscopes.* and, Deep learning convolutional neural network algorithms for the early detection. 2022.

74. *A survey on Image Data Augmentation.* Khoshgoftaar, Connor Shorten* and Taghi M. 2019.