Jimma University

Jimma Institute of Technology

Faculty of Computing and Informatics

Master of Science in Information Technology

INTEGRATION OF FEATURE FUSION STRATEGY ON EFFICIENT NET FOR SKIN CANCER DETECTION AND CLASSIFICATION

This Research Work is submitted to the School of Graduate Studies, Jimma University,

Jimma Institute of Technology, Faculty of Computing and Informatics in Partial Fulfillment of the Degree Master of Science in Information Technology

By

Seyfu Moges

December, 2023 G.C.

Jimma, Ethiopia

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Main Advisor: Dr. Worku Jifara

Co-Advisor: Mr. Dawud Yimer

DECLARATION

I hereby certify that the study "**Integration of Feature Fusion Strategy on EfficientNet for Skin Cancer Detection and Classification**" that I am presenting for this research is unique. This research has not been submitted as a partial fulfilment for any academic qualification at this university or any other, nor has it been utilized in any projects through any means. All the materials and resources utilized in this study have been duly recognized.

Seyfu Moges	________	29/12/2023 G.C.
Name	Signature	Date

This is to confirm that, to the best of my knowledge, the candidate's above declaration is accurate.

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ACRONYMS

CPU	Central Processing Unit
CNN	Convolutional Neural Network
DNA	Deoxyribonucleic Acid
DIP	Digital Image Processing
EHR	Electronic Health Records
GPU	Graphics Processing Unit
GLCM	Grey-Level Co Occurrence Matrix
ROI	Regions of Interest
SVM	Support Vector Machine
UV	Ultraviolet

ABSTRACT

Skin cancer is a disorder that arises from changes in healthy skin cells that give them the ability to become malignant. Due to a rise in predominance over the past ten years, it is currently placed among the top ten malignancies in terms of frequency. Patients who are unaware of skin cancer may not be encouraged to seek medical attention for minor skin discoloration because many people lack the knowledge required to notice it. One can lessen and manage the detrimental effects of skin cancer with an accurate diagnosis and prompt, efficient therapy. Investigating skin cancer lesions can be difficult due to their comparatively similar forms, complex expression of the disease, and susceptibility to subjective diagnosis. The obtained features from the multiple EfficientNet model tiers are combined using a feature fusion approach to solve this challenge. Therefore, in this study, a system was developed that could detect and classify skin cancer lesions into benign and malignant automatically by using a feature fusion strategy and EfficientNet algorithm with a transfer learning method. The image dataset was collected from a public dataset that is available on Kaggle and the total dataset used is 27560 from both classes benign and malignant. Pre-processing the skin lesions, extracting features using a pre-trained EfficientNet, feature concatenation, and classifying using deep learning EfficientNet algorithm are the primary components of this research. The study method was tested and yielded average results of ***93.4****% accuracy,* ***92.3****% precision,* ***94.8****% recall,* ***92.1****% specificity, and* ***93.5****% f1-score, respectively as well as confusion matrix achieved 1269(92.00%) true positives, 109(8.00%) false positives, 72(5.00%) false negatives, and 1306(95.00%) true negatives.*

.

Keywords: *Skin cancer, Deep learning, Feature fusion strategy, EfficientNet.*

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Skin problems are widespread in people. They are typically brought on by various organisms' cells, diets, and internal and external elements such as immune system disorders, hormones, and the hierarchical genetic collection of cells. These elements may contribute to skin disease concurrently or sequentially [1]. Globally, there are over 3000 recognized skin diseases [2]. Skin cancer is one of the skin diseases that appears on the skin. It is the expansion of aberrant cells with the potential to replication to further body parts. [3]. It has increased in prevalence during the past ten years, ranking among the most common cancers [4]. One of the biggest problems with skin illness in the body is the risk of infection from skin cancer [5]. While skin cancer is a non-communicable disease that is little understood in Africa, is prevalent there [6]. Annually more than 91,000 fatalities have been linked to this disease until now. Yet, regular screening and early detection, which can also help with accurate therapeutic interventions and life enhancement, can dramatically lower the death rate of skin cancer [7]. In the US, more than five million new instances of skin cancer are reported each year. In their lifetime, one out of every five Americans may receive a skin cancer diagnosis. Melanomas account for nearly ten thousand fatalities yearly in the USA alone. They also account for over 75% of all skin cancer-related deaths [8].

Dermoscopy is a non-invasive diagnostic technique used in dermatology to examine skin lesions or conditions. Intricate medical patterns of skin lesions or underlying skin features that are typically invisible to the unassisted eye can now be seen by dermatologists. However, there are no skin surface reflections in the improved dermoscopic images, which makes an accurate diagnosis of skin cancer [7]. As a result, one essential element for computer vision image classification is required.

The development of artificial intelligence (AI) enabled computer-aided diagnostics tools for skin cancer diagnosis has attracted a lot of attention lately. There is an urgent need for AI systems to support doctors in this field because of the rising prevalence of skin malignancies, low awareness among a growing population, and a lack of sufficient clinical experience and resources [9]. Deep learning beats almost all traditional methods for obtaining image features when dealing with large amounts of data [10]. Deep learning algorithms have surpassed all state-of-the-art methods now in use in several computer vision tests, including segmentation, detection, classification, etc. The development of supervised Deep Neural Network algorithms to handle these tasks has been made possible by the availability of computational power and vast amounts of labelled data [7]**.** Images of skin cancer from different classes have been recognized using deep learning algorithms. Convolutional Neural Networks (CNN) are used in these methods to classify skin cancer and record skin image appearance features. Likewise, one of the well-known CNN architectures is EfficientNet, which exhibited cutting-edge accuracy in the ImageNet competition. As EfficientNet design has shown a great enhancement in accuracy with fewer parameters [11].

Many machine learning and computer vision applications take advantage of data fusion. Features fusion is the term used to describe the complexity of combining multiple feature vectors [12]. In feature fusion, many feature information sources are combined to produce more salient feature information. Performances will vary depending on the feature fusion technique used. Accuracy can be increased by using an appropriate fusion technique [13].

In skin cancer classification, an image can yield a variety of properties, including texture, color, shape, and spatial information. By fusing these many qualities in a meaningful way, the feature fusion approach unifies them. A more thorough and insightful representation of the input images can be provided to the model by including feature fusion into the EfficientNet architecture. Thus, the model may be better able to differentiate between various kinds of skin lesions, producing skin cancer classification findings that are more precise and trustworthy. Therefore, the researcher used the feature fusion strategy and EfficientNet integration to detect and classify skin cancer to improve overall performance.

1.2 Statement of the problem

Skin cancer is increasing more swiftly and at a higher rate in countries like Australia, the USA, and Canada [14]. According to the American Cancer Society, melanoma will cause 7,180 deaths out of 106,110 patients in 2021 [12]. Skin cancer ranks as the most common cancer kind in the US. One of the most deadly and quickly spreading diseases is melanoma. Treating this cancer at its advanced stages is quite challenging. [1]. Skin cancer survival rates of 99% are associated with early diagnosis, which is critical to improving outcomes. However, survival rates are low if the disease gets deeper than the epidermis [9].

The substantial number of non-communicable diseases in Sub-Saharan Africa poses a significant challenge to public health in the region. Despite the continued prevalence of infectious diseases in Africa [15]. Traditional skin cancer diagnosis, particularly for melanoma, presents several challenges. The diversity of different skin tones makes the identification of skin cancer more difficult and intricate [16]. One of the main issues is the need for reliable methods to monitor disease progression or treatment resistance, as highlighted in a 2018 paper by [17]. The authors discuss the potential of liquid biopsy as a predictive biomarker to guide therapeutic decisions, but also note the challenges of using this method, such as the strict criteria for the phenotypic nature of circulating melanoma cells and the instability of circulating tumor DNA in blood. Another challenge is the diagnosis of desmoplastic melanoma, an uncommon variant that can mimic scar and other benign proliferations, making it difficult to diagnose, especially in small biopsy specimens. This was discussed in a 2013 paper by [18].

On the other hand, the conventional diagnostic methods are also considered expensive and inconvenient, and their effectiveness is subject to the expertise of the dermatologist and the availability of a highly equipped environment. This was highlighted in a 2020 paper by [19], who also discussed the potential of computerized systems for melanoma detection and classification, despite the challenges these systems currently face. The use of handheld confocal microscopy for skin cancer diagnosis has been explored, as discussed in a 2016 paper by [20], particularly useful for diagnosing tumors on curved surfaces of the face and around the eyes, but it also has its limitations. Finally, a 2017 paper by [21], discussed the potential of genetic expression profiling (GEP) assays to resolve diagnostic dilemmas in melanocytic tumors. However, the authors also noted the challenges associated with GEP validation and testing.

In general, traditional methods for finding skin cancer require dermatologists to do a physical examination, which takes time, and the diagnostic accuracy depends on the dermatologist's level of expertise. Setting up a computer-based system that uses different image processing techniques could be seen as a replacement for human examination [13].

For the following reasons, determining the exact diagnosis of a certain skin condition can be difficult. Firstly, correct diagnosis is a significant difficulty for healthcare professionals due to the disease's complicated appearance. Secondly, the lesions may be difficult to distinguish from one another just based on visual cues. In addition to this, the diagnosis methods are tedious, time-consuming, require an extensive understanding of the domain, need being qualified experts, and vulnerable to subjective diagnosis [22]. Due to light reflections from the skin's surface, variations in color brightness, and unique shapes and sizes of the lesions, it is also challenging to analyze this skin lesion. Therefore, to increase dermatologists' precision and skill in early skin cancer diagnosis, automatic identification of the illness is necessary. [16].

The 1990s saw the introduction of early CNN versions for computerized systems, which are used to automatically learn imaging features through regions of interest (ROIs) without explicit user input. However, there is still work to be done on illustrating medical images through deep-learning techniques [23]. Hence, the abundance of biomedical data presents both enormous potential and difficulties for healthcare research [24]. There are a lot more problems with using AI to diagnose skin cancer in lesions of the skin datasets of different modalities due to deep learning algorithms typically need a sizable amount of balanced, diversified, and excellent training information that reflects every category of skin lesions to increase diagnostic accuracy [9]. A lack of data and an emphasis on standardized activities like dermoscopy and histological image categorization have prevented previous efforts in dermatological computer-aided categorization from having the generalization capacity of medical practitioners. Also, Photographic images like those from smartphones, for instance, show fluctuations in illumination, angle, and zoom, which significantly increases the difficulty of classification [8].

Generally, incorporation of the feature fusion technique on a pre-trained EfficientNet model is a general way that this research can increase the performance of human skin cancer detection and classification.

1.3 Research Question

1. How does the adoption of feature fusion techniques improve the performance of the skin cancer classification model?
2. What are the performance aspects of the skin cancer classification model when analyzed by different evaluation metrics?

3. How does healthcare practitioners use the feature fusion technique built on the EfficientNet model to diagnose skin cancer practically?
4. How to compare the fusion approach of EfficientNet with the existing skin cancer classification model?

1.4 Objective of the Study

1.4.1 General Objective

The main aim of this study is to investigate Human Skin Cancer using the integration of a feature fusion strategy on EfficientNet.

1.4.2 Specific Objectives

- To adopt feature fusion techniques for increasing the performance of the skin cancer classification model.
- To evaluate the efficiency of the skin cancer classification model by the utilization of many different metrics, confusion matrix, accuracy, precision, recall, specificity, and F1 score.
- To employ a graphical user interface for skin cancer classification.
- To compare the feature fusion approach integrated in EfficientNet with the existing skin cancer classification models.

1.5 Scope and limitations

The work entails creating the feature fusion approach and incorporating it into the EfficientNet architecture to classify skin cancer. This may include designing the fusion mechanism, training the model using labelled skin lesion images, and optimizing the model's performance. The study compares the performance of the feature fusion strategy integrated into EfficientNet with the current skin cancer classification works. On the other hand, there are some potential limitations may include such as dataset bias (there could be intrinsic biases in the training and evaluation dataset, such as an overrepresentation of particular skin types or lesion kinds), generalization (the results of the study might only apply to the particular dataset and study settings), and

Computational requirement (when it comes to training and inference, EfficientNet models can be computationally demanding and involving significant computer resources).

1.6 Significance of the Study

Patients, dermatologists, the medical community, and the nation as a whole can all gain major benefits from the incorporation of the feature fusion technique in EfficientNet for skin cancer classification. The following are some possible benefits:

For patients:- Enables the patients to obtain an accurate diagnosis, and early detection of the disease, reduces anxiety, and awareness about the disease as well as improves a delay to take treatment timely, because computerized based diagnosis is much faster than the manual system.

For Dermatologists: - Provide more reliable diagnostic support, reducing the risk of misdiagnosis and improving patient care. Additionally, it is time-saving and allows them to focus their time and expertise on more complex cases or other aspects of patient care.

For the health sector:- The time and effort needed for human examination are decreased by the speedier and automated analysis of skin lesions made possible by the inclusion of the feature fusion technique. Improved productivity and shorter patient wait times might result from healthcare providers being able to manage more cases due to their enhanced efficiency.

For a country: It is used as a benchmark for other researchers and can contribute to early detection and prompt treatment. This can lead to improved public health outcomes, reduced morbidity, and decreased mortality rates associated with skin cancer. In addition to this, it increases accessibility to healthcare and allows individuals in remote or underserved areas who may have limited access to specialized dermatologists as this study can empower individuals to take proactive measures in protecting their skin, such as practising sun safety and seeking regular screenings. This may result in a decrease in the prevalence of skin cancer and the financial strain it places on the healthcare system.

Hence, the detection and classification issues related to human skin cancer are resolved as a result of this work.

1.7. Organization of the Thesis

Chapter 1 Under this section, the background of the study, statement of the problem, research questions, objectives of the study, scope and limitations, significance of the study, and organization of the thesis are included.

Chapter 2 Discusses the general human skin structure, skin cancer, digital image processing, deep learning and its applications, CNN, EfficientNet model architecture, feature extraction, feature fusion strategy, and summary of related work.

Chapter 3 Encompasses the methods used for this research such as the conceptual framework of the study (research design), dataset preparation, data preprocessing, creating train, validation, and test data segments from the dataset, feature extraction, feature fusion, building the fused model, train and test the model, performance evaluation and classification algorithm of skin cancer.

Chapter 4 This section includes the experimental setup and a summary of experimental results, performance evaluation results, comparative analysis with the existing work, and discussion.

Chapter 5 Lastly, illustrations for the conclusion, recommendation, and forthcoming tasks are provided.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Overview

Skin cancer is a disorder caused by changes to healthy skin cells' features that enable them to become malignant. DNA damage leads cells to divide uncontrollably into atypical forms, which is what causes skin cancer [3]. The Skin Cancer Foundation estimates that one in five Americans will get skin cancer in their lifetime, and the WHO believes that skin cancer can be detected in every third instance of cancer [25].

A computer-based system is one of the key topics of research in diagnostic radiology and medical imaging. Numerous computational techniques are being developed for use in the identification and/or characterization of lesions found using different medical imaging modalities [26]. Deep learning, a form of machine learning, uses numerous layers of computational modules arranged in hierarchical structures to categorize (predict) patterns and model high-level abstractions of the underlying data [27]. Most academics believe that within the next 15 years, deep learning-based apps will replace humans and that most diagnostics will be performed by intelligent machines [28].

EfficientNet is an operational and boosting method for convolutional neural networks that achieves uniform scaling across all dimensions like depth, breadth, and resolution. The core principle of the EfficientNet architecture is to uniformly scale the various dimensions of the network- width, depth, and image resolution. Eight different CNN models are grouped under the umbrella of EfficientNet: EffectiveNet-B0 to B7 [29].

A technique known as "feature fusion" allows for the seamless integration of pertinent data that has been taken from a collection of training and test images. Learning all of an image's characteristics to describe its rich internal information is made easier by feature fusion [30].

Nowadays, the most rapidly evolving diagnostic technique in health care is image processing. Digital image processing techniques are being used in different fields of interest, such as medical visualization, law enforcement, and agricultural product quality inspection [31].

2.2 Human Skin Structure

One of the biggest systems in the human skeleton, the skin regulates body temperature and shields the body from light and extreme heat [14]. It is made up of hair shafts, which tie hair strands to the skin and shield us from the elements. It also controls body temperature by secreting sweat, which cools the body, and it allows us to feel touch, heat, and cold.

Skin cancer is the result of aberrant skin cell turnover, which might manifest as a hard red nodule, a scaly growth that crusts over, or an open sore that fails to heal up [12]. The dermis, hypodermis, and epidermis are the three main layers that makeup skin. The general skin structure is explained in Figure 2.1 [31].

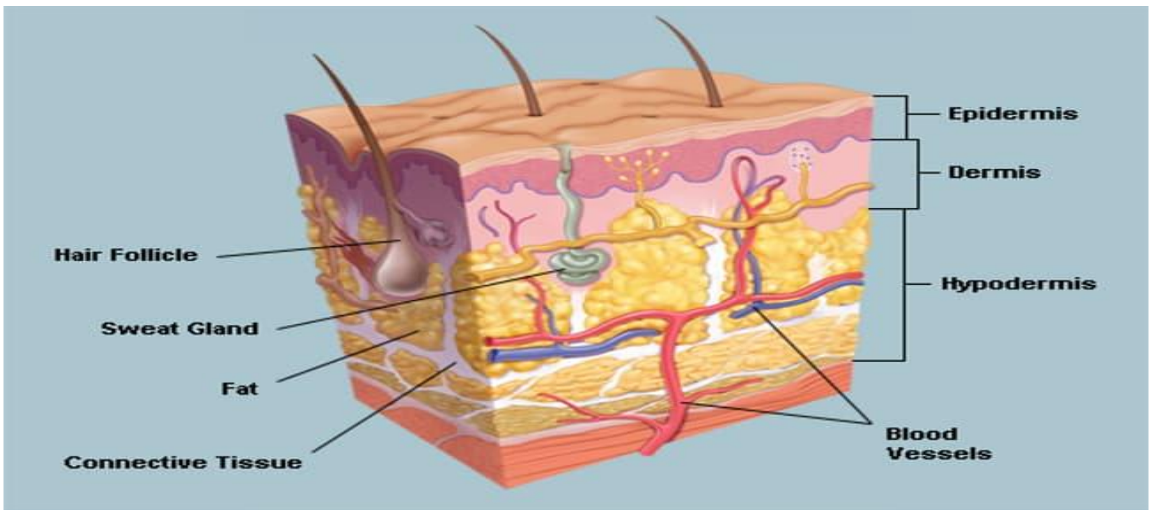

Figure 2.1; The general structure of the skin

Epidermis

The top layer of the skin in humans is called the epidermis, and it is made up of basal lamina and multilayered squamous cells. The skin contains basal cells, which are flat, spherical cells that sit beneath squamous cells [32]. The majority of skin cancers begin in the epidermis, or top layer of skin.

Three primary cell types can be found in the epidermis:

Squamous cells: The epidermis' outermost layer contains these flat cells. As new cells develop, they shed continuously. The type of skin cancer that can develop in these cells is called squamous cell carcinoma.

Basal cells: These tissues are located underneath the squamous tissues. They divide, reproduce, eventually flatten out, and go higher up in the epidermis to become new squamous cells to replace the dead ones that have shed off. The skin cancer that develops in basal cells is known as Basal cell carcinoma.

Melanocytes: These cells produce melanin, a brown pigment that gives skin its color and shields the skin from some of the sun's UV radiation that can damage it. The skin cancer that develops in melanocytes is called Melanoma.

The main function of the epidermis is to protect your body, avoid potentially harmful things, and exclude what your body needs for normal function.

Dermis

The skin layer that sits above the subcutaneous layer and below the epidermis is called the dermis. It is composed of elastic and fibrous tissue and is the thickest layer of the skin. As a result, it gives the skin elasticity and strength. The dermis's main function is to sustain the epidermis and make it possible for the skin to flourish. Because of the existence of blood vessels, sweat glands, sebaceous glands, hair follicles, and nerve endings, it also performs many additional functions. Nerve endings in the dermis can detect touch, temperature, pressure, and pain stimuli. There are more nerve endings in highly sensitive portions of the skin than in less sensitive areas due to the variation in the number of nerve endings in the various skin sections. The production of sweat in reaction to specific situations, such as heat and stress, is attributed to the dermal sweat glands. Sweat helps cool the body to preserve homeostasis when it evaporates from the skin.

Hypodermis

Out of the three layers of skin, the hypodermis is the deepest layer and is mainly composed of fatty acids that act as an insulator, temperature regulator, nutrient store, and barrier against damage to surrounding structures. The sub-cutis is another name for this stratum. Its main function is retaining the body's heat and protecting your important interior organs by containing sweat glands, fat, and collagen cells.

2.3 Challenges of Skin Disease

Many people around the world experience numerous skin conditions, which historically have been a frequent disease in people. The unseen hazards associated with these conditions frequently include an increased chance of skin cancer, depressive symptoms, and a lack of self-confidence [33]. Clinical knowledge and visual perception are key components in skin disease diagnosis. Computerized skin-image analysis technologies, in contrast, lack the subjectivity, precision, and repeatability that characterize human visual diagnosis [22].

2.4 Human Skin Cancer

Skin cancer is one of the most common cancers in humans; it begins on the skin due to abnormal cell proliferation that is easily invasive and spreads to other parts of the body [32]. New skin cells normally form when existing skin cells are damaged or age and die. Rapid cell development, including the possible development of abnormal cells, occurs when this process isn't working properly. This collection of cells may be benign or malignant. Benign cells don't spread or pain, but if they aren't found and treated in time it is said to be malignant, and they could spread to nearby tissue or other areas of your body. Overexposure to sunlight, especially when it causes sunburn and blistering, is the primary cause of skin cancer. Your skin's DNA is harmed by ultraviolet (UV) radiation from the sun, which leads to the formation of aberrant cells. There are many types of skin cancer. These are:-

1. Basal cell carcinoma

The most common cause of basal cell cancer is sun exposure, which also affects our hands, faces, arms, legs, tongues, ears, and even the bald areas on top of our heads. Basal cell cancer is the most common type of skin cancer worldwide. It usually doesn't spread to other parts of the body, grows slowly in most cases, and isn't potentially fatal.

Figure 2.2; Basal cell carcinoma

2. Squamous cell carcinoma

It most frequently appears on skin that has been exposed to the sun, such as the face, legs, hands, ears, mouths, arms, and bald places on the head. There are two other areas where this skin cancer can develop: mucous membranes and the genitalia.

Figure 2.3; Squamous cell carcinoma

3. Melanoma

Melanoma is the most fatal type of skin cancer, accounting for the majority of deaths connected to the disease [5]. Skin cancer has the highest mortality rate. The liver, spleen, brain, and lungs are just a few of the organs where melanoma cells frequently metastasize [34]. The human body can acquire melanoma in any location. Even our eyes and internal organs may develop it. It mainly affects the legs in women, although it often affects the upper back in men. This type of skin cancer is the most deadly since it can spread to other places of the body.

Figure 2.4; Melanoma

4. Actinic Keratoses

A rough and frequently bumpy patch or lesion that develops on the skin is known as an actinic keratosis. The scalp, backs of the hands, face, ears, backs of the forearms, and neck are the areas where these lesions are most frequently found. Actinic keratoses grow over a long period. They typically manifest in adults 50 years of age or older. In the US, 58 million people have at least one actinic keratosis [35].

5. Benign Keratoses-like lesions (bkls)

Seborrheic Keratoses (SK), another name for benign keratoses, are the most frequent skin tumours. Most elderly persons who have it tend to have it in sun-exposed locations. Usually, it arises after the age of 40. Although they frequently affect the back or chest, they can also affect the scalp, face, arms, and legs. Seborrheic keratoses develop slowly, either alone or in clusters. In most cases, seborrheic keratoses appear on average once in a person's lifetime. No malignant potential exists in them.

6. Dermatofibroma (df)

Skin cancer known as dermatofibroma (DF) is uncommon. DF typically begins in the dermis and develops gradually. Other body regions are rarely affected by it. DF has an excellent survival rate due to its infrequent metastasis. However, therapy is crucial. Without medical intervention, DF can penetrate far into the fat, muscle, and even bone. Treatment may be difficult if this occurs.

7. Melanocytic nevus (nv)

Melanocytic nevus is produced by cells that are in charge of manufacturing melanin, which results in a malfunction of the melanocytes. It is a condition that affects the skin cells and causes pigmentation. More often known as moles, these are typically non-cancerous in origin. These moles may have been present since birth or they may have appeared later in life.

8. Vascular Lesions (vasc)

Based on behaviour, histologic findings, and genetics, vascular lesions might be classified as tumours or malformations. Vascular malformations are divided into four subcategories: simple, combined, those of a major designated vessel, and those connected to defects. They frequently have blue skin discoloration.

Generally, the types of skin cancer can be categorized into two main parts Malignant which includes melanoma and Benign consists of the rest seven types of skin cancer.

2.5 Image Processing

Image processing is the way of digitizing an image and applying particular techniques to it to extract some useful information from it. The normal interpretation of all images by the image processing system is that they are all 2D signals when a specific set of predefined signal processing algorithms is used [36]. With the aid of computer algorithms, a digital image is processed in digital image processing (DIP) to produce an improved image by extracting some important information. Processes at the low, middle, and high levels are included in DIP. Low-level processes include things like image sharpening, contrast improvement, and noise reduction. Medium-level processes include actions like segmentation, where a picture is the input and image characteristics are the outputs. High-level processes are used to interpret a collection of attributes. Any image processing application must first go through the fundamental procedures of image collection, preprocessing, segmentation, feature extraction, and categorization. In general, many applications for image processing may use different methodologies.

2.6 Application of Deep Learning

Deep learning is a novel field in machine learning that leverages neural network models to simulate human brain function and extract features through this modelling. Due to its benefits, such as its high recognition accuracy and strong feature extraction capabilities, deep learning is extensively used in image recognition [37]. In a variety of fields, such as object detection, speech recognition, picture segmentation, and machine translation, deep learning (DL) has redefined state-of-the-art performances since 2006 [27]. In addition to this, targeted advertising, interpreters, helpers for natural language, self-driving car prototypes, and other human-centred smart-world technologies have all helped deep learning gain widespread acceptance [38].

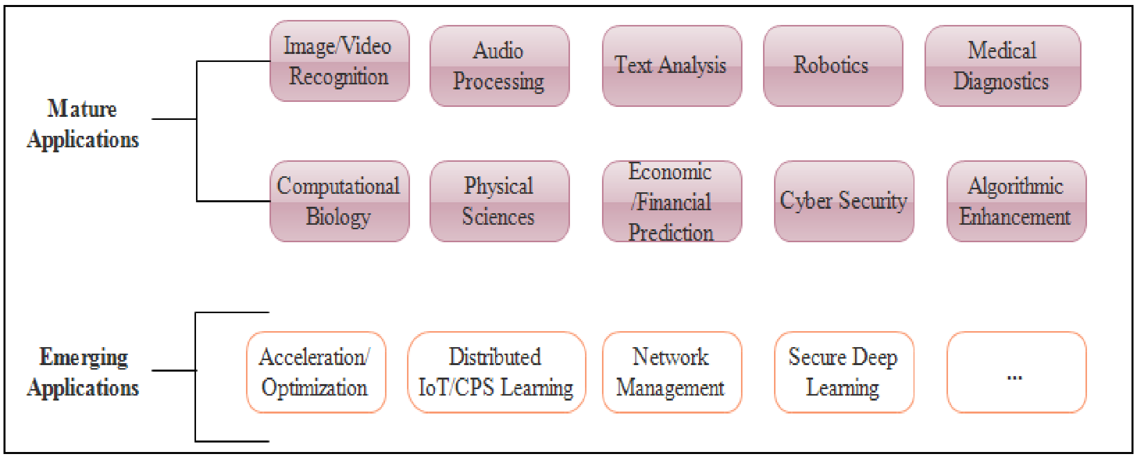

Figure 2.5; Deep Learning Application

2.7 Convolutional Neural Network (CNN)

CNN has demonstrated exceptional performance in processing video and images ever since GPU (Graphics Processing Unit) computing methods became widely available [39]. Yann LeCun, et al. invented the Convolutional Neural Networks (CNN), an upgraded sort of neural network [5]. An essential kind of deep neural network that is successfully applied in computer vision is the convolution neural network. It is utilized for picture classification, compiling a collection of input images, and image recognition [4]. CNN has been utilized to recognize and classify images successfully in recent years. Generic CNNs only extract features from one image [13]. The most popular feature extraction methods in CNN are the convolutional layer, pooling layer, and activation function. The fully connected network then categorizes the gathered data. [13].

1. Convolutional Layer

The initial layer is used to extract the various features from the input images. The input image and a filter with the specific size MxM are convolutioned mathematically in this layer. When the filter is moved across the input image, the dot product between the filter and various portions of the image is calculated according to the filter's size (MxM). CNN's convolution layer transfers the output to the subsequent layer after applying the convolution operation to the input. The CNN's convolutional layers preserve the spatial connection between the pixels [40].

2. Pooling Layer

The technique known as "pooling" layers lowers the dimensionality of the data by combining the outputs of neuron clusters from one layer into a single neuron [33]. Similarly, by obtaining a summary statistic from the surrounding outputs, the pooling layer substitutes for the network's output at specific locations. As a result, the representation's spatial size is reduced, which reduces the amount of computation and weights needed. Every slice of the representation is individually handled for the pooling operation [41].

3. Fully Connected Layer

A fully connected layer, whose structure is similar to that of conventional neural networks, has neurons that are completely connected to every activation in the layer above. All that separates convolutional layers from fully-connected layers is that the former is connected to only a fraction of the input. An N-dimensional vector is produced by the fully connected layer using the input volume as its input [42].

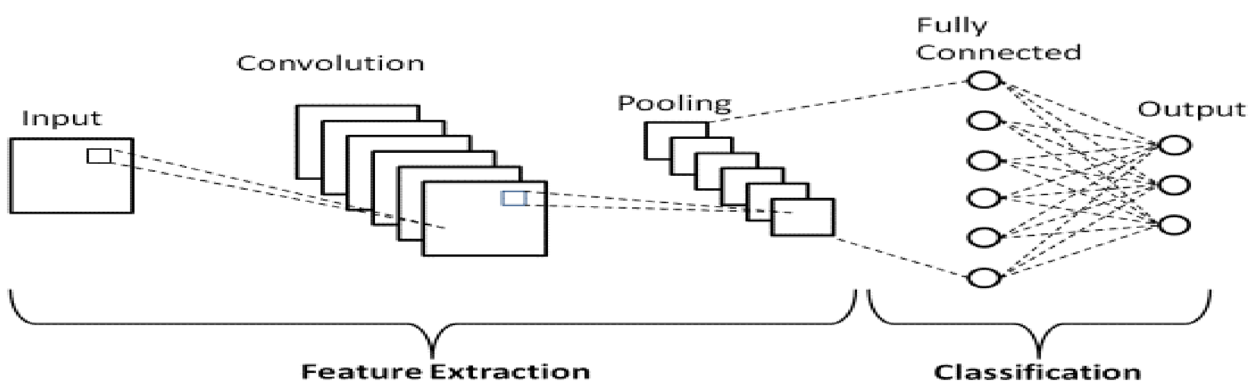

Figure 2.6; General structure of CNN

2.8 EfficientNet Model Architecture

Deep learning has recently been employed extensively for the diagnosis of numerous medical conditions. In a similar vein, some research has been done on utilizing deep learning to diagnose illnesses of the skin [43]. EfficientNet, first presented by Tan and Le in 2019, is one of the most accurate models for both ImageNet and typical image categorization at the moment. It requires the fewest FLOPS for inference [44]. A compound coefficient is used by the DCNN scaling and design method known as EfficientNet to equally scale each variable's width, depth, and resolution. With the EfficientNet scaling strategy, network width, depth, and resolution are equalized using a set of predetermined scaling factors, as opposed to the standard method which scales these variables randomly [45].

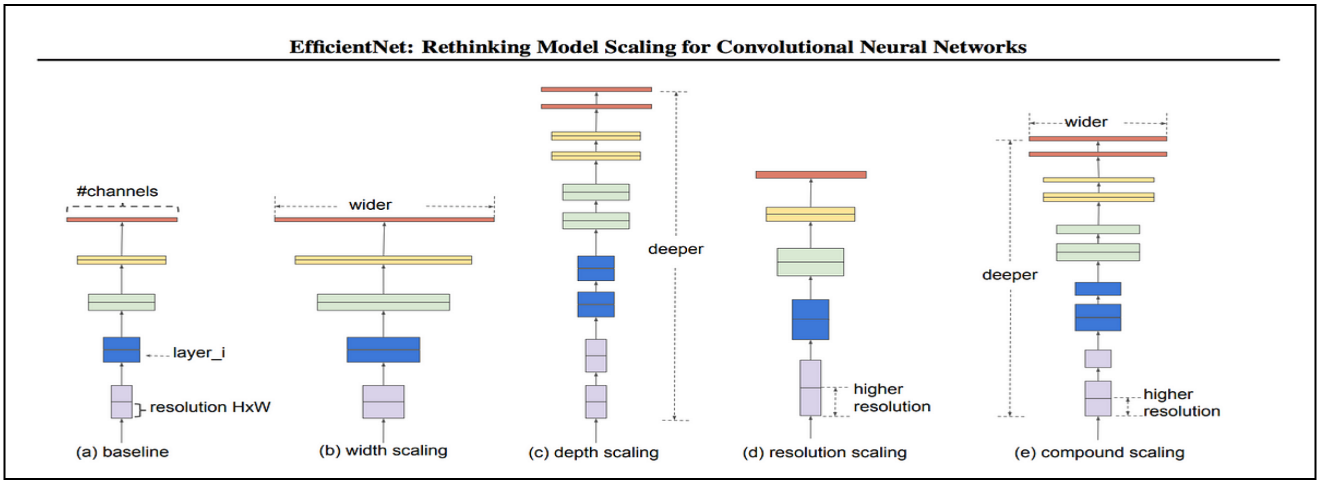

Figure 2.7; EfficientNet Model Architecture

2.9 Extracting features

A series of vectors with image features that represent the original image are created by extracting features from image data [22]. It is one of the most important issues in artificial intelligence. The objective is to recognize and categorize an image's key elements. The most important step in image classification is examining the properties of picture features and classifying numerical features [46].

2.10 Feature Fusion Strategy

One of the newest methods for data processing is information fusion [47]. The fusion of several distinct feature information sources to provide more salient feature information is known as feature fusion. It is important to choose a realistic feature fusion method because different feature fusion techniques would result in varying effectiveness [13]. The process of combining feature vectors from training images that were taken from the shared weight network layer with feature vectors made up of other numerical data is known as feature fusion [48].

Several studies have proposed different methods of feature fusion for medical image classification. For instance, a 2021 study by [49], proposed a Distant Domain Transfer Learning (DDTL) model that uses a Distant Feature Fusion (DFF) classification model for medical image classification, specifically for COVID-19 diagnosis using lung CT images. The DDTL model achieved a 96% classification accuracy, which was 13% higher than non-transfer algorithms and 8% higher than existing transfer and distant transfer algorithms. In 2018, [50], proposed a deep learning model that integrates Coding Network with Multilayer Perceptron (CNMP), which combines high-level features extracted from a deep convolutional neural network and some selected traditional features. This model achieved an overall classification accuracy of 90.1% and 90.2% on two benchmark medical image datasets, which were higher than the current successful methods. A 2022 study by [51], proposed a novel neural architecture search method DLS-DARTS for glioma grading during surgery. This method uses two learnable stems for multi-modal low-level feature fusion and achieved an area under the curve of 0.843 and an accuracy of 0.634, outperforming manually designed convolutional neural networks and a state-of-the-art neural architecture search method for multi-modal medical image classification.

Another study by [52], proposed a model fusion framework based on online mutual knowledge transfer (MF-OMKT) for breast cancer histopathological image classification. This model achieved an accuracy range of 99.27% to 99.84% for binary classification and 96.14% to 97.53% for multi-class classification. Also, a 2021 study by [53], proposed a two-level framework for the classification of digital breast tomosynthesis (DBT) datasets. This framework uses a basic multilevel transfer learning (MLTL) based framework and a feature extraction based transfer learning (FETL) framework. The FETL framework looks at three different feature extraction techniques to augment the MLTL based framework performance, achieving an area under the receiver operating characteristic (ROC) curve of value 0.89.

Furthermore, [54], proposed a multiscale feature fusion model for skin lesion classification using a two-stream network, DenseNet-121 and improved VGG-16, achieving a test accuracy of 91.24%. The study [55], proposed a method for multiclass skin lesion classification using deep learning feature fusion and an extreme learning machine, achieving an accuracy of 93.40% and 94.36% on HAM10000 and ISIC2018 datasets respectively. Similarly [56], proposed a fully automated approach for multiclass skin lesion segmentation and classification using the most discriminant deep features, achieving an accuracy of 90.67% on the HAM10000 dataset.

In conclusion, feature fusion in medical image classification has been shown to significantly improve classification accuracy in various medical imaging tasks.

2.11 Related Work

In “Advanced Skin Diseases Diagnosis Leveraging Image Processing”; the authors suggested employing a grey-level co-occurrence matrix (GLCM) to extract features and SVM for detecting four skin conditions: rosacea, melanoma, psoriasis, and acne [57]. Even though their system recognizes four skin illnesses, the performance is still slightly poor because they did not apply feature fusion techniques and had issues with the feature extraction strategy.

“Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network”; for the classification of melanoma and benign lesions CNN was proposed and they got 81% accuracy [58]. Even though they have used CNN; the accuracy is somewhat poor. .

“A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning”; the authors perform the diagnosis of skin lesions like acne, eczema, psoriasis, and benign and malignant melanoma as well as use SVM for classification. The accuracy achieved is 83% [59]. Even if their method identifies four skin diseases listed above, still the accuracy is somewhat not good due to a problem with the techniques of feature extraction strategy.

In “Vision-Based Classification of Skin Cancer using Deep Learning”; Skin cancer is categorized by the author as benign or malignant. The algorithm used in this paper is fine-tuned pre-trained VGG-19 and it has 78% of overall accuracy. The accuracy of this paper is poor and classifies skin cancer as benign and malignant only [60].

“Skin Cancer Classification Model Based on VGG19 and Transfer Learning”; in this research work, the authors used VGG-19 with transfer learning and classified the skin cancer as Dermatofibroma and Basal Cell Carcinoma, and Benign Keratosis-like Lesions (BKL). In this case, the author does not include hair removal under pre-processing conditions, and other types of skin cancer are not considered in his work [61].

Many researches was done on human skin cancer classification using standard images for instance; [58] was proposed classification of melanoma and benign lesions by Analysis of Clinical Images Using CNN with an accuracy 81%; this result was claimed by author [62] they proposed Skin cancer disease classification image using deep learning solutions by using inceptionv3, resnet, and VGG19 with an accuracy result of 86.9%; similarly [1], argue that with an accuracy percentage of 90.9 by using Xception than both Resnet50, and VGG16 to classify automatic Malignant and Benign Skin Cancer Using a Hybrid Deep Learning Approach. Therefore, the proposed works showed promising results for the diagnosis of different skin diseases from clinical images. However, most of the works were not using feature fusion and a graphical user-interface that helps for healthcare sector in our country in order to apply practically. However; this study incorporates feature fusion technique on a pre-trained EfficientNetB7 model as a general way to improve the performance of human skin cancer detection and classification.

Summary of Literature Review On Skin Cancer Classifications							
No.	Title	Authors	Published		Significance	Methodology	Gap
			Journal	Year			
1.	Skin cancer diagnosis based on optimized convolutional neural network	[5]	Artificial Intelligence In Medicine	2020	Early detection of skin cancer.	Optimal CNN	Performance analysis was tested only by two methods; Dermquest and DermIS No feature fusion.
2.	Boosted Efficient-Net: Detection of Lymph Node Metastases in Breast Cancer Using Convolutional Neural Networks	[63]	MDPI	2021	To predict and categorize breast cancer lymph node metastases. Additionally, techniques for feature fusion and attention improve the semantic data	By CNN methods and Random Center Cropping and EfficientNet.	Only classify the lymph node metastases in BC and test the RPCam dataset. No feature fusion.

					from visual features retrieved by CNN.		
3.	Skin Lesion Segmentation and Multiclass Classification Using Deep Learning Features and Improved Moth Flame Optimization	[56]	MDPI	2021	The study was useful for accurate lesion segmentation.	Deep learning-based saliency segmentation method and CNN feature optimization were used with improved moth flame optimization	In this study, deep models did not avoid getting irrelevant image features.
4.	Artificial Intelligence-Based Image Classification for Diagnosis of Skin Cancer: Challenges and Opportunities	[9]	Comput Biol Med	2020	The studies served to aid dermatologists in their work and improve their capacity to identify skin cancer.	Document review	The only review on Artificial Intelligence. No feature fusion.
5.	Deep Semantic Segmentation and	[64]	IEEE Access	2020	Early skin lesion detection,	Ensemble CNN models with YOLOv2 and	The performance parameter was only four.

	Multi-Class Skin Lesion Classification Based on Convolutional Neural Network				segmentation, and classification were made easier by the study.	ResNet-18, 3-D semantic segmentation models.	No feature fusion.
6.	Hybrid feature fusion and machine learning approaches for melanoma skin cancer detection	[12]	Creative Commons CC	2022	Determine whether a skin cancer is melanoma or not.	CNN feature based on VGG19 and hybrid feature extractor (HFE) are used.	Focuses on classifying skin cancer as either melanoma or non-melanoma and employs a machine-learning technique with Vgg19.
7.	Skin Cancer Detection: A Review Using Deep Learning Techniques	[4]	Int. J. Environ. Res. Public Health	2021	Demonstrate the DL techniques for skin cancer early detection.	Systematic article review	Only document reviews.
8.	Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion With CNN Deep Features	[65]	Intelligent Healthcare Technology	2019	The study was exploring a breast CAD method.	Using US-ELM clustering and CNN deep features.	Only on breast cancer.

9.	Remote Diagnosis and Triaging Model for Skin Cancer Using EfficientNet and Extreme Gradient Boosting	[43]	Hindawi Complexity	2021	For the diagnosis and remote triaging of skin cancer, the study was used by medical professionals and patients.	EfficientNetB3 deep learning model.	The proposed model was not tested by multiple datasets. It needs another best model to improve its performance. Only use EfficentnetB3. No feature fusion.
10.	Skin Cancer Classification Framework Using Enhanced Super Resolution Generative Adversarial Network and Custom Convolutional Neural Network	[66]	Open access	2023	The study was used by dermatologists to examine and classify the class of skin cancer.	CNN on the HAM10000 (Human vs. Machine) database	The study conclusion was made depending on accuracy percentage; rather than other performance metrics. No feature fusion.
11.	Melanoma Skin Cancer Detection Using EfficientNet and Channel Attention	[11]	Research Gate	2021	The study was able to identify and classify melanoma skin	A deep transfer learning and EfficientNet	Exclusively employing the pre-trained EfficientNetB3 and EfficientNetB5 models for training datasets. Additionally,

	Module				cancer.		the images' batch size was 16.
12.	Automatic Melanoma Diagnosis in Dermoscopic Imaging Base on Deep Learning System	[67]	Mid Sweden University, Sundsvall	2021	The findings assisted dermatologists in creating automated processes that offer more trustworthy diagnoses of melanoma skin cancer.	Deep CNNs based on the Yolo network.	Dataset images were less and focused only on melanoma image analysis. No feature fusion.
13.	Skin Lesion/Cancer Detection Using Deep Learning	[68]	International Journal Of Applied Engineering Research	2020	The research built a unique deep-learning architecture that focuses on the timely evaluation of skin cancer.	Deep CNN	The ratio of the dataset was 80% to 20%. Furthermore, it solely divides melanoma kinds into benign and malignant classes. No feature fusion.

14.	Skin Cancer Classification Using Deep Learning Models	[69]	International Conference on Agents and Artificial Intelligence	2022	The classification issue with melanoma was helped by the study.	VGG16 and modified InceptionV3.	Only focuses on melanoma skin cancer and it utilizes a smaller number of image datasets. No feature fusion.

CHAPTER THREE

3. MATERIALS AND METHODS

In this section, proposed architecture, dataset preparation, data preprocessing, creating train, validation, and test data segments from the dataset, feature extraction, feature fusion, building the fused model, training and testing the model, performance evaluation, classification algorithm, comparison analysis and discussion are explained in detail.

3.1 PROPOSED ARCHITECTURE

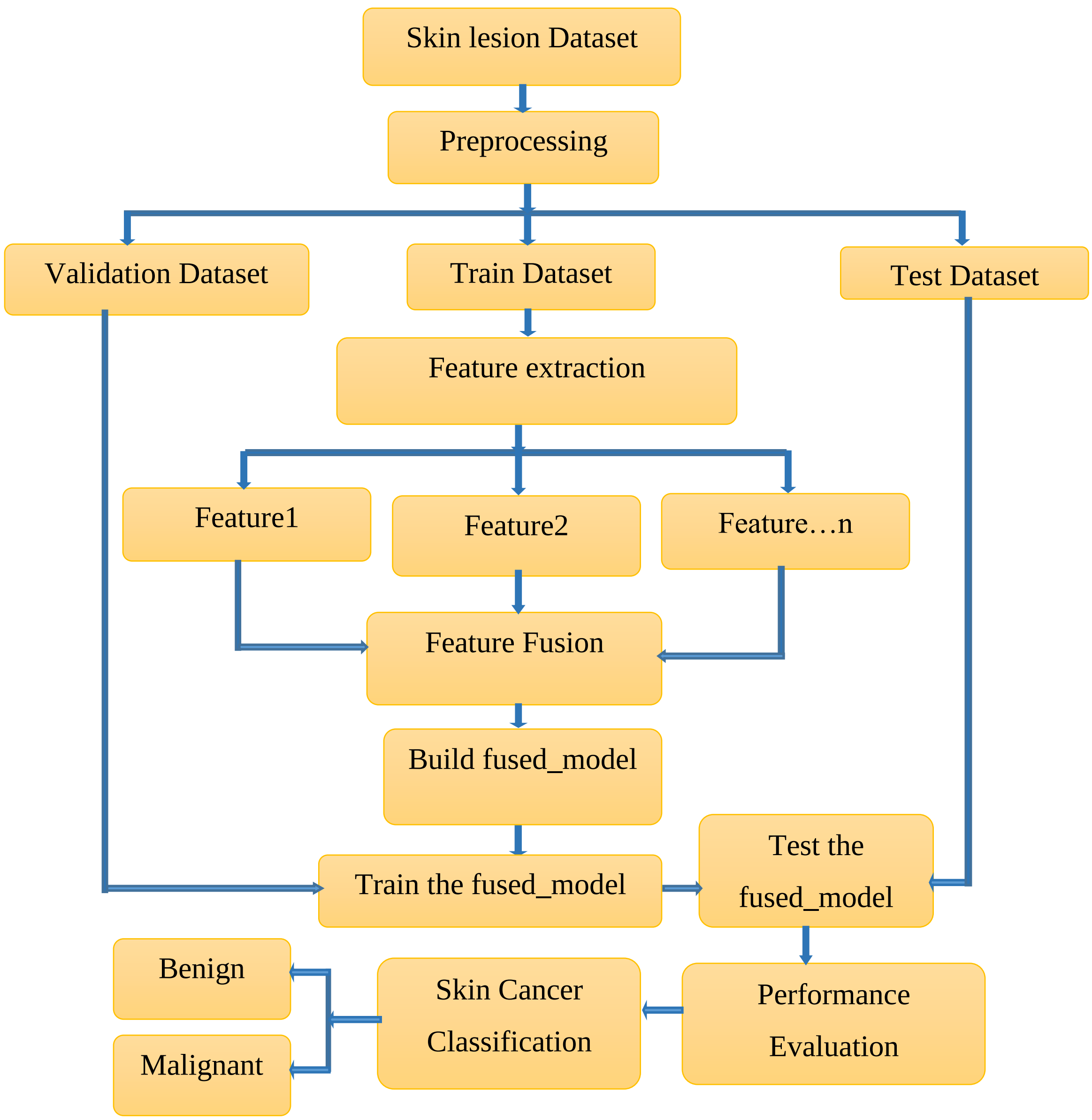

Figure 3.1; Block diagram of a proposed architecture

3.2 Dataset Preparation

The lack of training datasets is one of the main obstacles to the widespread use of deep learning in medical imaging since the size and calibre of the datasets greatly influence a deep learning classifier's ability to perform well in classification [28]. Various aspects impacting image quality have been addressed in the context of classification accuracy of deep neural networks, and poor image quality has been identified as a significant factor influencing the performance of deep neural networks in computer vision applications. An obvious way to lessen the detrimental effect of low image quality on improving classification accuracy is to use quality images [70]. Selective, reliable Computer Vision data sets are increasingly readily available online due to the difficulties in obtaining sufficient data for training a machine learning model. Obtaining sufficient amounts of appropriate, high-quality data to train algorithms is one of the difficulties faced by businesses engaged in Computer Vision initiatives as well as Several companies have developed and made available an array of already labelled or pre-labelled sets of data in the past few years [71].

Data is a crucial component of this work since the feature fusion approach and EfficientNet are used to advance the classification performance of human skin cancer. A public dataset of skin cancer lesions that was available online from Kaggle was used for this research and the size of the dataset was 27560 skin lesion images. The ratio used for benign and malignant is 1:1 which means both classes have an equal number of datasets. Malignant images are labelled as "one" or (1) and benign images as "zero" or (0) respectively. There are numerous compelling arguments for selecting the Kaggle dataset that is accessible online. Firstly, the Kaggle dataset is a standardized dataset collection that is intentionally developed to diagnose different types of diseases in image processing and it is an active area of research. Secondly, the Kaggle image datasets have better quality and quantity than the images captured manually. Thirdly, it minimizes the time and other resources to collect those datasets manually, In addition to this; the datasets available online have countless significance for creating a resilient deep learning detection and classification architecture.

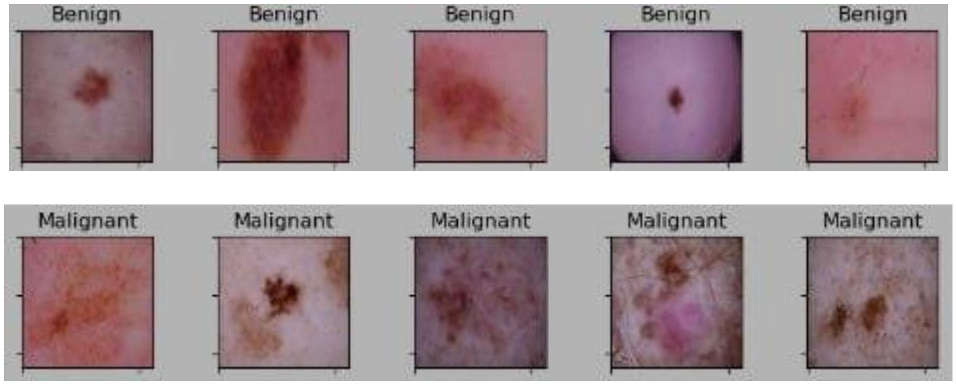

Figure 3.2 Sample of benign and malignant skin lesions

3.3 Skin lesion preprocessing

The primary goal of the image processing approach is to minimize the noise in the image by applying various types of filters [72]. To provide accurate results, some strategies are applied to eliminate unnecessary and distorted pixels from images [12]. Preprocessing of image data is a technique for enhancing the quality of an image by eliminating extraneous image data [73]. There are many unnecessary and undesired components in the actual format of scanned medical images and metadata. A deep learning CNN requires a little pre-processing in contrast to conventional classification methods, which rely on manually created filters. One benefit of CNN is its independence from human interference in learning filters. To improve classification accuracy, the researcher deals with a variety of preprocessing approaches in this work. These are dataset acquisition, loading the datasets, resizing, normalization, and data augmentation [74]. The skin cancer datasets are collected from a publicly available online website that is https://www.kaggle.com/datasets.The dataset was load from a specific directory on the Python environment for further investigation. In order to speed up model convergence, the size of the images was resized to the standard average width and height at 224*224 pixels, which is the recommended image size for the majority of pre-trained models like EfficientNet. All pixel values was normalized between 0 and 1 or -1 and 1 to enhance the model's performance during training. To achieve a normalized value between 0 and 1, normalization includes dividing each pixel value by the highest value (for example, 255) [75]. This can be stated as:

$$normalize\_value = \frac{original\_value}{maximum\_value} \quad \text{...Equation 3.1}$$

Several data augmentation techniques are employed in this research project, including fill mode, rotation range, width and height shift range, shear range, zoom range, and horizontal flip [76].

3.4 Training, Validation, and Test Dataset

In this study, the datasets are randomly divided into train, validation, and test data of 80% for training, 10% for validation, and 10% for testing. Based on this ratio there are 22,048 skin cancer images for training, 2756 for validation, and 2756 for testing out of a total dataset of 27560 skin cancer datasets from two classes benign and malignant.

Table 3.1; Class level available skin lesion dataset across training, validation, and test data

Class	Benign	Malignant
Training Samples	11024	11024
Validation Samples	1378	1378
Test Samples	1378	1378
Total Samples of each class	13,780	13,780

3.5 Transfer Learning

A technique used by ANNs called transfer learning enables a system to retain the knowledge gained during one training job and apply it to another related activity. For instance, the skills acquired when learning to distinguish tigers may be applied to learning to recognize cats. Fine-tuning CNN models that have been trained using natural images are utilized in medical image applications as a type of transfer learning [77]. Transfer learning is a well-liked and useful method for training a network on a tiny dataset. Its basic assumption is that, if learnt on a sufficiently large dataset, general principles can be applied across datasets that appear to be unrelated [78]. In this study, integration of a feature fusion strategy was applied on a pre-trained EfficientNet as well as by modifying the top classification layer that is a transfer learning mechanism rather than training the model from scratch; because transfer learning is preferable to robust the performance of the model.

3.6 Feature Extraction with a pre-trained EfficientNetB7

The ability to transfer knowledge between domains is greatly aided by trained computer vision models. It meets the need for enormous quantities of labelled images for training. Pre-trained models can be used in two different situations, especially on the size of the dataset and the resources that are available for computation [79]. By uniformly scaling down the model while using a uniform scaling strategy to all network dimensions, including depth, width, and resolution, EfficientNet has been proposed to increase the accuracy and efficiency of CNN. As the EfficientNet's model count grows, its accuracy progressively improves. They are known as EfficientNets because they outperform earlier Convolutional Neural Networks in terms of accuracy and efficiency. [80].

Feature extraction is the stage of the research that is most notable and significant. It is performed on the dataset's images to minimize the number of features [1]. The link between the unprocessed pixel data and the class labels can be directly learned by a CNN. It does not require human experience for feature extraction, in contrast to the approach utilized in machine learning [81]. Generally, extracted features are descriptive and commonly texture features, color feature size or shape features, etc. The proposed work used a pre-trained EfficientNetB7 as a feature extractor from different layers of a pre-trained EfficientNetB7.

3.7 Feature Fusion

Applying feature fusion, one can create a compact representation of integrated features, and properly describe the rich internal information of the image's features [82]. When working with multi-modal data, such as mixing visual features from images with textual features from captions or combining features from various layers of a convolutional neural network (CNN), feature fusion frequently occurs in computer vision. In this study, the researcher combined the features using feature concatenation techniques. Data from several levels or branches of a neural network's structure can be joined using the fusion technique concatenation, which is frequently employed in deep learning models [83]. It is a prominent option for feature fusion in deep learning models for many reasons, including:

3.7.1 Preservation of Information

Concatenation keeps all the data from each network level or branch. The model can interact with both high-level and low-level information by concatenating the features, capturing a more thorough representation of the input data.

3.7.2 Increased Model Capacity

As features from several levels are combined, concatenation expands the model's capacity. For difficult problems where it's important to use various abstraction layers to generate precise predictions, this can be helpful.

3.7.3 Flexibility

The flexibility of concatenation allows for the non-linear combining of features from many levels or branches. Because of its adaptability, the model can capture complex correlations between variables and possibly enhance performance as a whole.

3.7.4 Simplicity

The operation of concatenation is simple to use. It doesn't add any extra trainable parameters, which makes computations quick and lowers the chance of overfitting.

3.8 Build the fused model

The next step after feature fusion is the model-building process. The model building includes the inputs, output, or prediction. In this study, a base model of the EfficientNet model input is used as an input and the output or prediction is the result of concatenated features and the classification layers combination. Subsequently, the model is assembled using the suitable optimizer Adam, together with the relevant optimizer settings such as learning rate, binary_cross_entropy loss function, Relu and Sigmoid activation functions. The activation function is adequate if it helps the system learn and do challenging tasks, which increases the neural network's power. In order to enable the network to adjust to nonlinear features from the input images, the activation functions receive the feature maps from the convolution layer [84]. Mapping the input to the output is the primary role of any activation function in a neural network-based model. The sigmoid activation function connects the output to the interval [0, 1] using real values as its input which is used for binary classification.

3.9 Train the fused model

To train the model with the feature fusion strategy on EfficientNet for skin cancer classification, there are some steps to follow like dataset Preparation, Preprocessing, Feature Extraction, Feature Fusion, Model building. Finally, the compiled model is trained using the fit () method by initializing some parameters of a fit () method like epoch size, batch size, callbacks, and so on.

3.10 Test the fused model

Testing is required in order to assess how well the fused model performs. The test dataset can be used to assess how well the developed model performs in relation to the training dataset. The trained model is loaded, the test data is preprocessed, and an inference is performed by the researcher in order to test the model trained with the feature fusion approach on EfficientNet for skin cancer classification to generate the model's predictions.

3.11 Performance evaluation metrics

Confusion Matrix

It is a matrix that shows the relationship between the model's categorization and its real label (predicted label). One of four categories best describes the Confusion Matrices' findings. When the model accurately predicts the positive class of an image, it is called a True Positive (TP). When the model incorrectly predicts an image's positive class (FP), a False Positive is produced. A True Negative (TN) is an image in which the model correctly predicts its negative class. When the model forecasts the negative class (FN) incorrectly, it results in a false negative. [81].

Accuracy

Accuracy evaluates the model's total correct classification rate, which is important for analyzing the overall effectiveness of the model. Accuracy in the context of classifying skin cancer refers to the percentage of instances—both benign and malignant—that are correctly classified out of the total number of cases.

$$\text{Accuracy} = \frac{\text{Total\_Number\_of\_Correct\_predictions}}{\text{Total\_Number\_of\_samples}} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{......Equation 3.2}$$

Precision

The ratio of accurate positive predictions to all positive predictions made by the model is known as precision. It pertains to the model's ability to accurately identify true positive cases or correctly classify a certain form of skin cancer as benign or malignant in the context of skin cancer categorization. It denotes the possibility that a favourable prediction will come true.

$$\text{Precision}=\frac{True\_Positive}{Total\_Positive\_Values}=\frac{TP}{TP+FP} \quad \text{Equation 3.3}$$

Recall (Sensitivity)

Recall, sometimes referred to as sensitivity or true positive rate, is the ratio of true positive predictions to the total number of actual positive cases in the dataset. It assesses a model's capacity to locate and catalogue every incident of skin cancer. It shows the percentage of positively detected cases that are positive.

$$\text{Recall}=\frac{True\_Positive}{True\_Positive\_plus\_False\_Negative}=\frac{TP}{TP+FN} \quad \text{Equation 3.4}$$

Specificity

Specificity is a metric that assesses how well a model can detect negative events or the actual negative rate. The percentage of actual negative cases that the model accurately detected is quantified. Higher specificity values reflect a model that is more accurate at differentiating between positive and negative cases since they show a lower rate of false positives. Conversely, lower specificity scores show a larger rate of false positives, suggesting that the model may be classifying data inaccurately.

$$\text{Specificity}=\frac{True\_Negative}{True\_Negative\_plus\_False\_Positive}=\frac{TN}{TN+FP} \quad \text{Equation 3.5}$$

F1-Score

The F1 score is calculated by adding precision and recall harmonically. When the dataset is unbalanced or when both precision and recall are crucial, it offers a balanced measurement of both measures and is especially helpful. Since the F1 score considers both the recall and precision of positive case identification, it is crucial for classifying skin cancer cases.

F1-Score $= \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})}$…………...……...………………...… Equation 3.6

3.12 Classification algorithm

Convolutional neural networks are a type of deep learning network that learns directly from data. (CNN or ConvNet). CNNs are very useful for classifying, categorizing, and recognizing objects in photos. Additionally very helpful is the ability to categorize time series, signals, and audio data [85]. EfficientNet joined the leading edge on the ImageNet competition with 84.4% performance and a 66M parameter computing load. Like any other model, transfer learning reduces computing time and power for EfficientNet. In doing so, it offers greater precision than a lot of popular models [86].

Hence, in order to distinguish between benign and malignant skin cancer, the EfficientNetB7 algorithm was used in this study in conjunction with the feature fusion technique via a transfer learning tactics.

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1 Experimental Setup and Tools

The researcher carried out the experiments in Python programming language version 3.11, which is one of the most widely used programming tools today for deep learning and data science. The computational resource limitation is one of the challenges while implementing this research work. Deep learning models need a lot of time for training time and good computational resources like GPU whenever the dataset size is a huge and complex model. In addition to this, it has emerged with financial burdens because there are costs per service usage, and therefore it was far more expensive to purchase GPU. Due to this reason, the CPU is used as an alternative to the GPU to train the model on an Anaconda Jupyter notebook which is free. A total of 27560 skin lesion dataset was used. The dataset has two classes benign and malignant as well as this data was divided into training set, validation set and test set based on 80% for training, 10% for validation and the remaining 10% for testing. Based this 22048 skin lesions for training, 2756 for validation and 2756 for test was used. Some preprocessing techniques are utilized such as image resizing, normalization and augmentation. All skin lesions are resized in 224*224 pixels which is the recommended image size due to its fast model convergence and normalized accordingly using one of the normalization technique that is dividing each pixel value the maximum value which is 255 as well as data augmentation was used to expand the dataset artificially. The model architecture used in this study was EfficientNetB7 which is extended form of EfficientNet and achieves better performance in image classification. Two models was used, the first one is the basic EfficientNetB7 and the second one is integration of feature fusion strategy on EfficientNetB7. Some hyperparameters are used to robust the classification performance. Performance metrics like confusion matrix, accuracy, precision, recall, specificity and f1-score were utilized. In addition to this, the proposed work includes the graphical user interface system in order to deploy to the health sector for practical usage.

Furthermore, to carry out this research, a few hardware and software tools are utilized. The explanation and justification of these tools are provided in the section below as follows. Hardware tools that are used for the implementation of this research are a hard disk: for the storage of the datasets and, a CPU: for training the models, Software tools are used for the implementation of this study to write the code, debug, visualize results, and document the research process for reporting. The Software tools used in this research work are:-

Anaconda with Jupyter Notebook: is a desktop-based application that helps to configure, load Python API, and write Python code using a CPU processing unit.

Keras: is one specific deep learning framework. It is not a competitor of TensorFlow because it runs "on top" of TensorFlow. It is a sophisticated API that supports TensorFlow operations. It is user-friendly, has easy extensibility supports modularity, and works with Python as a high-level framework or API [62].

Tensorflow: - It is a machine learning platform to build a model and deploy it in client environments like other real-world applications. It supports ML, deep learning, and flexible numerical computation. TensorFlow offers optional CUDA and SYCL extensions and enables computation on numerous CPUs and GPUs. Additionally, TensorFlow Lite offers an Android Neural Network and is intended for embedded and mobile machine learning [38].

Python: - Python is a programming language used for doing different software applications (APIs) as well used for research purposes.

4.2 Hyperparameters Used

Hyperparameters are parameters whose values are set before beginning the model training process. A few extended parameters For example, convolutional neural network (CNN) and recurrent neural network (RNN) models in deep learning might have hundreds or even thousands of hyperparameters [87]. There some many hyper parameters used in this research. These are:-

Batch Size: - The number of training examples or data samples that are concurrently processed in a single forward and backward pass is referred to as the "batch size". Batch size 32 is used.

Number of epochs: is the number given or initialized during the training to set the maximum number of iterations the model training undergoes.

Optimizers: - Adam is used with the optimizer parameter or learning rate of 0.0001.

Dropout Rate:- The dropout rate used in this paper is 0.5

Table 4.1; Hyperparameters used for training the Model

Parameters	Value
Batch size	32
Number of epochs	10
Steps per epoch	689
Optimizer	Adam (learning rate=0.0001)
Dropout Rate	0.5

4.3 Model Summary

The details of the model summary like the layer type used, output shape as well as the parameters of the pre-trained EfficientNetB7 with and without features fusion strategy mentioned in this portion. The model summary of a modified pre-trained EfficientNetB7 without a feature fusion approach is shown in Table 4.2. It just adds top classification layers like the Dense layer and a few other layers like the input layer, GlobalAveragePooling2D, BatchNormalization, and Dropout layer. There are 2,625,537 trainable parameters out of a total of 66,725,265 parameters.

Table 4.2; Model summary of EfficientNetB7 without feature fusion

```
Model: "model_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_8 (InputLayer)        [(None, 224, 224, 3)]     0         
                                                                 
 efficientnet-b7 (Functiona  (None, 7, 7, 2560)        64097680  
 l)                                                              
                                                                 
 global_average_pooling2d_5  (None, 2560)              0         
  (GlobalAveragePooling2D)                                       
                                                                 
 dense_13 (Dense)            (None, 1024)              2622464   
                                                                 
 batch_normalization_8 (Bat  (None, 1024)              4096      
 chNormalization)                                                
                                                                 
 dropout_8 (Dropout)         (None, 1024)              0         
                                                                 
 dense_14 (Dense)            (None, 1)                 1025      
                                                                 
=================================================================
Total params: 66725265 (254.54 MB)
Trainable params: 2625537 (10.02 MB)
Non-trainable params: 64099728 (244.52 MB)
_________________________________________________________________
```

Table 4.3 shows the model summary of how a feature fusion approach is integrated into a pre-trained EfficientNetB7, and the enhanced or modified top classification layer of a pre-trained EfficientNetB7 like input layer, Dense layer, GlobalAveragePooling2D, AveragePooling2D, BatchNormalization, Flatten layer, Concatinate and Dropout layer. There are also 13,109,249 trainable parameters from 77,207,953 total parameters.

Table 4.3; Model summary of EfficientNetB7 with feature fusion

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 224, 224, 3)]	0	[]
efficientnet-b7 (Functional)	(None, 7, 7, 2560)	64097680	['input_2[0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2560)	0	['efficientnet-b7[0][0]']
average_pooling2d (AveragePooling2D)	(None, 3, 3, 2560)	0	['efficientnet-b7[0][0]']
flatten (Flatten)	(None, 2560)	0	['global_average_pooling2d[0][0]']
flatten_1 (Flatten)	(None, 23040)	0	['average_pooling2d[0][0]']
concatenate (Concatenate)	(None, 25600)	0	['flatten[0][0]', 'flatten_1[0][0]']
dropout (Dropout)	(None, 25600)	0	['concatenate[0][0]']
dense (Dense)	(None, 1024)	26215424	['dropout[0][0]']
batch_normalization (BatchNormalization)	(None, 1024)	4096	['dense[0][0]']
dropout_1 (Dropout)	(None, 1024)	0	['batch_normalization[0][0]']
dense_1 (Dense)	(None, 1)	1025	['dropout_1[0][0]']

Total params: 90318225 (344.54 MB)
Trainable params: 26218497 (100.02 MB)
Non-trainable params: 64099728 (244.52 MB)

4.4 Results

The researcher adopted the following approach to evaluate the proposed CNN model's effectiveness in skin cancer classification. The metrics measured during the training of the dataset were Accuracy, Validation Accuracy, Loss, and Validation Loss. These metrics were calculated for training and validation data. The accuracy and loss of both training and validation data of the EfficientNetB7 model without feature fusion and with feature fusion of this study were mentioned in Tables 4.4 and 4.5.

As shown in Table 4.4, a pre-trained EfficientNetB7 model without feature fusion achieves 83.5% training accuracy and 88.6% validation accuracy. The corresponding training and validation losses are 0.36 and 0.27. On the other hand, as shown in Table 4.5, the pre-trained EfficientNetB7 by applying a feature fusion strategy scores a better accuracy than the basic pre-trained EfficientNetB7 which is 92.32% average training accuracy and 93.32% average validation accuracy. Additionally, the training and validation loss also have improved with 0.21 and 0.18 respectively.

Table 4.4; Loss and Accuracy Value of EfficientNetB7 without feature fusion

Matrix	**Value**
Training Accuracy	0.835
Training Loss	0.36
Validation Accuracy	0.886
Validation Loss	0.27

Table 4.5; Loss and Accuracy Value of EfficientNetB7 with Feature Fusion

Matrix	**Value**
Training Accuracy	0.92
Training Loss	0.21
Validation Accuracy	0.93
Validation Loss	0.18

The model was trained using Python 3.11 with CPU Accelerator for 10 iterations on the Anaconda Jupyter Notebook. Figures 4.1 and 4.2, illustrate model accuracy and loss graphs for a pre-trained EfficientNetB7 model without feature fusion. The highest validation accuracy measured was 88.6% and the validation loss was 0.27.

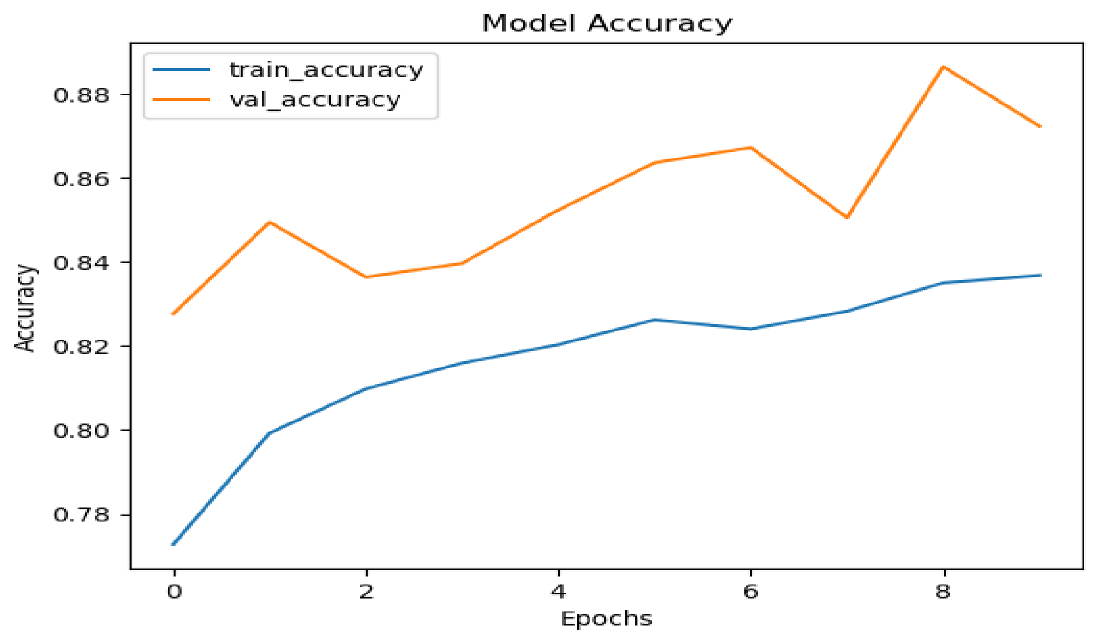

Figure 4.1; Model accuracy graph of the training without fusion

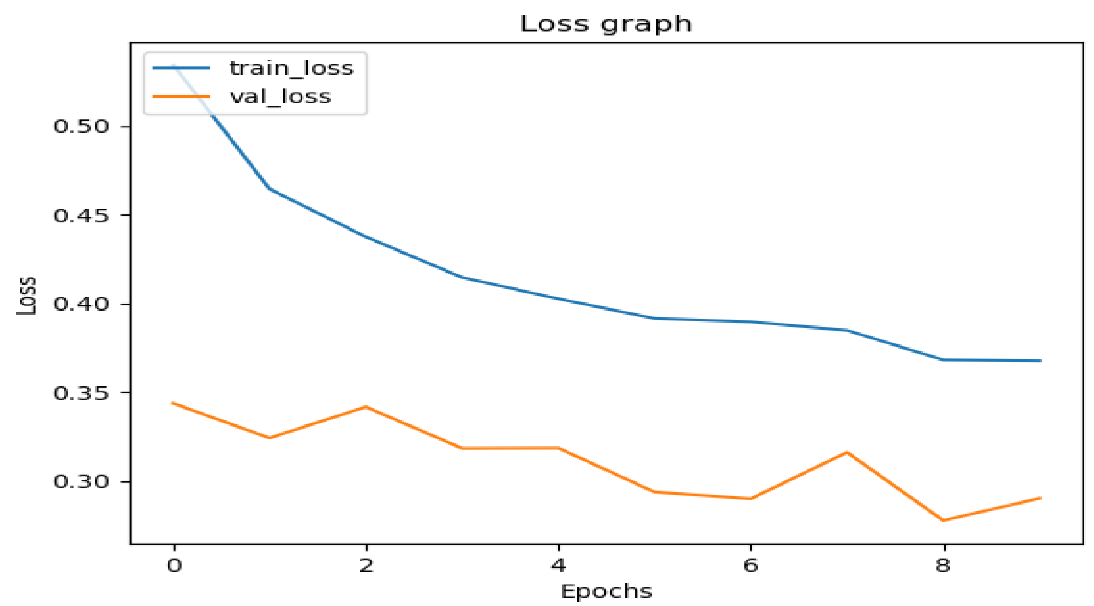

Figure 4.2; Loss graph of the training without fusion

The training and validation accuracy of a pre-trained EfficientNetB7 is shown in Figure 4.3 with the integration of a feature fusion approach on the y-axis and its corresponding epochs on the x-axis, and it achieves the highest accuracy of 92.32 and 93.32, respectively. Figure 4.4, shows the training and validation loss of 0.21 and 0.18, respectively.

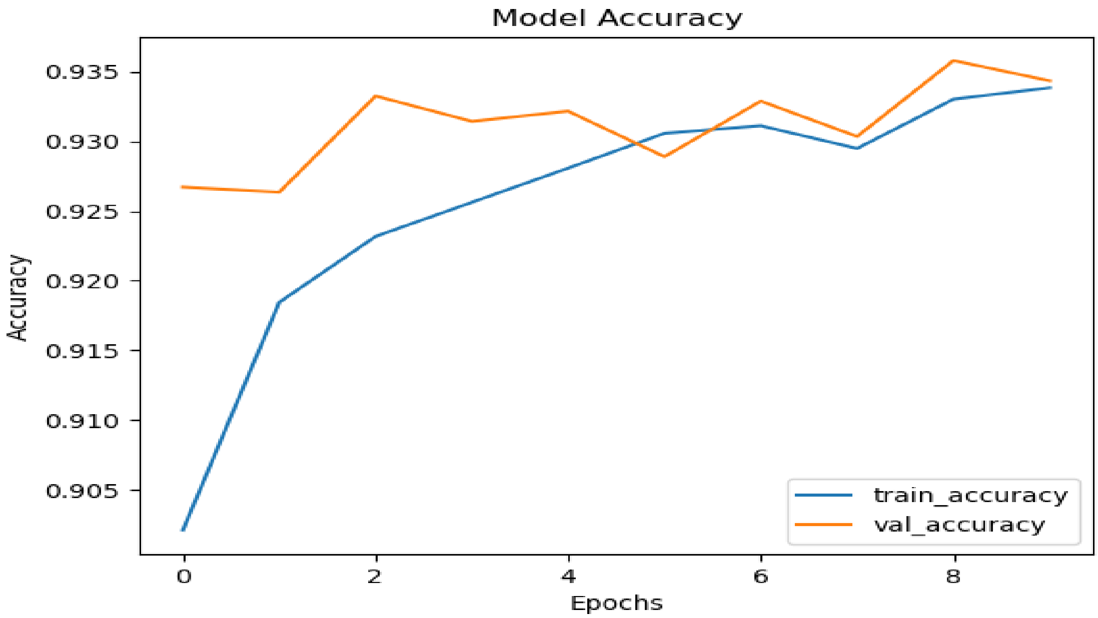

Figure 4.3; Model accuracy graph of the training with fusion

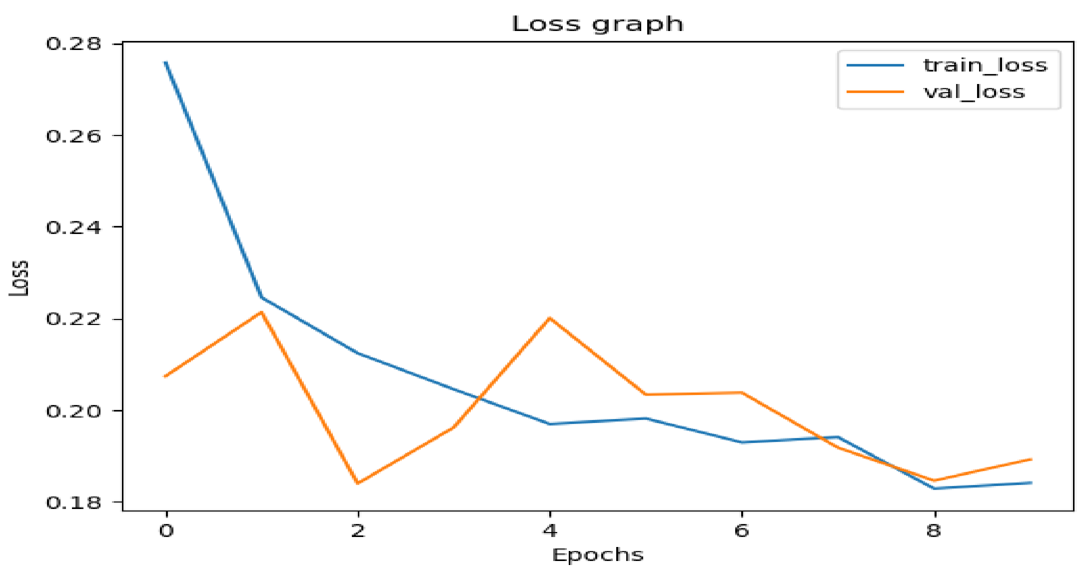

Figure 4.4; Loss graph of the training with fusion

4.5 Performance Evaluation

The study uses the Confusion Matrix, Accuracy, Precision, Recall, Specificity, and F1-score to evaluate the performance of the suggested model. The images were tested with a mini-batch size of 32. The confusion matrix is a table that is used to evaluate the performance of a classification model by showing the number of true positives, true negatives, false positives, and false negatives. In Figure 4.5, the confusion matrix is obtained from the two classes mentioned below and has four values. These values are represented in a 2x2 matrix, with the rows representing the actual class of skin cancer and the columns representing the predicted class. The pre-trained EfficientNetB7 model without feature fusion strategy achieves a confusion matrix of 1261(92.00%) true positives, 117(8.00%) false positives, 175(13.00%) false negatives, and 1203(87.00%) true negatives. This means 1261 benign skin cancer images are correctly classified out of 1378 images and 1203 malignant skin cancer correctly classified from a total of 1378 images. Similarly, 117 images of benign skin cancer are mistakenly identified as malignant skin cancer and 175 malignant skin cancers are also incorrectly categorized as benign skin cancer. Based on the results in Figure 4.5 the number of malignant skin cancer predicted as benign is greater than the number of benign skin cancer classified as malignant. This is a serious problem because malignant skin cancer is a highly dangerous and deadly type of skin cancer that spreads to other parts of the body if it is left untreated earlier. So, as much as possible reducing the number of incorrect predictions for malignant skin cancer as benign skin cancer to zero is expected to save the lives

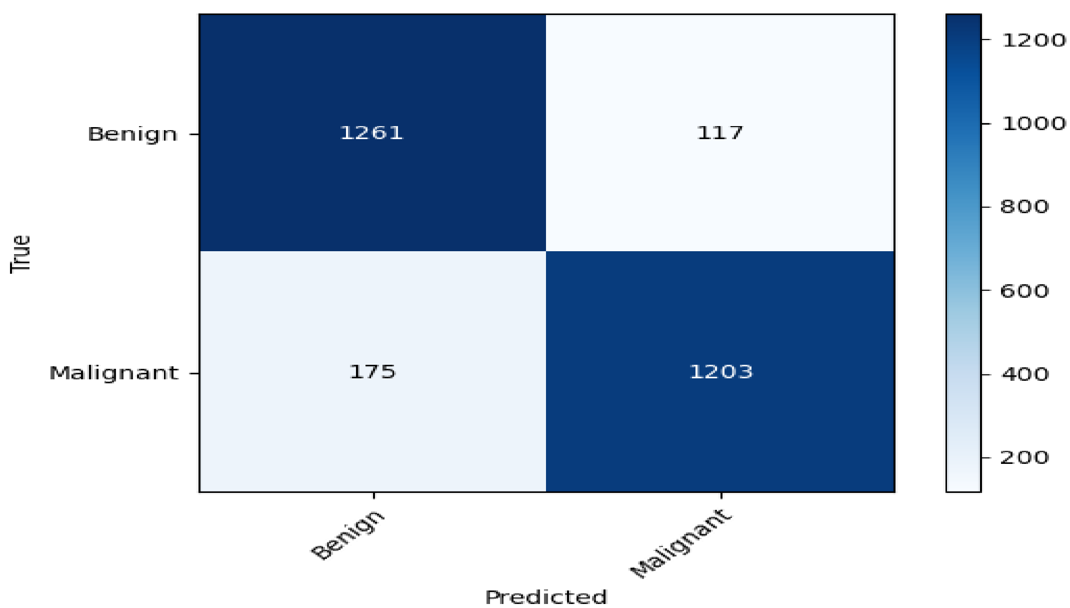

Figure 4.5; Confusion matrix representation without feature fusion

The confusion matrix shown in Figure 4.6 has four values: 1269(92%) true positives, 109(8%) false positives, 72(5%) false negatives, and 1306(95%) true negatives. Similar to Figure 4.5, 1269 benign skin cancer images are correctly predicted from 1378 images, and 1329 malignant skin cancer images are correctly categorized out of 1378 images. On the other hand, 109 benign skin cancer images are incorrectly classified as malignant and 72 malignant skin cancer images are incorrectly predicted as benign skin cancer. In this case, the number of malignant skin cancer which is classified falsely as benign skin cancer is only 72 images or 5% out of the total 1378 cancer test dataset. There is a significant improvement from the pre-trained EfficientNetB7 model without feature fusion that falsely predicts 175 cancer images as benign cancer to 72 images. So, the integration of a feature fusion strategy on a pre-trained EfficientNetB7 for skin cancer classification outperforms in terms of reducing the number of improper predictions of malignant skin cancer as benign skin cancer.

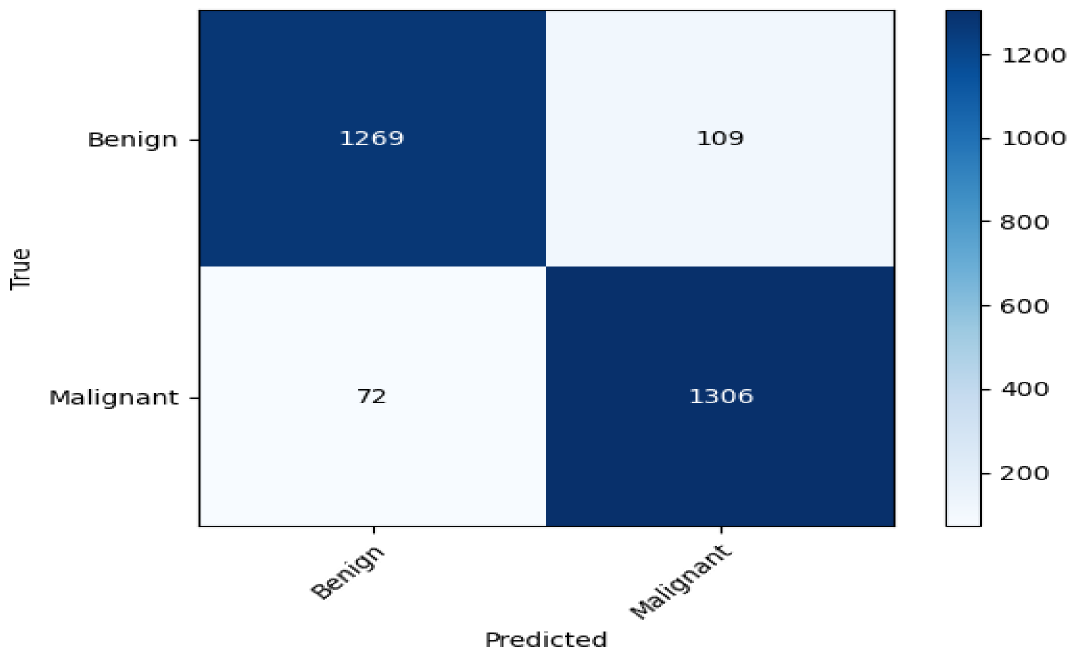

Figure 4.6; Confusion matrix representation with feature fusion

As indicated in the class-wise classification performance metrics of Table 4.6, on average 88% precision, 92% recall, and 90% f1 score is achieved for benign and 91%, 87%, and 89% for malignant respectively using a pre-trained EfficientNetB7 without a feature fusion strategy. On the other hand, in Table 4.7, the class-wise performance of the proposed method of integrating feature fusion strategy on EfficientNetB7 obtained on average 95% precision, 92% recall, and 93% f1 score for benign and 92% precision, 95% recall, and 94% fl-score for malignant using a pre-trained EfficientNetB7 with a feature fusion strategy. Overall, the fusion model used for skin cancer classification outperforms when compared with the pre-trained EfficientNetB7 without fusion.

Table 4.6; Class-level performance of EfficientNetB7 without feature fusion

	precision	recall	f1-score	support
Benign	0.88	0.92	0.90	1378
Malignant	0.91	0.87	0.89	1378
accuracy			0.89	2756
macro avg	0.89	0.89	0.89	2756
weighted avg	0.89	0.89	0.89	2756

Table 4.7; Class-level performance of EfficientNetB7 with feature fusion

	precision	recall	f1-score	support
Benign	0.95	0.92	0.93	1378
Malignant	0.92	0.95	0.94	1378
accuracy			0.93	2756
macro avg	0.93	0.93	0.93	2756
weighted avg	0.93	0.93	0.93	2756

Table 4.8 shows the overall model performance of EfficientNetB7 without feature fusion and scored 89.4 % accuracy, 91.1% precision, 87.3% recall, 89.2% f1-score, and 91.5% specificity. On the other hand, a pre-trained EfficientNetB7 using a feature fusion technique performs better than the findings listed in Table 4.8, as shown in Table 4.9 and achieved the best performance of 93.4% test accuracy, 92.3% precision, 94.8% recall, 93.5% of f1-score and 92.1% specificity which is 4%, 1.2%, 7.5%, 4.3% and 0.6 better than the pre-trained EfficientNetB7 model without feature fusion respectively.

Table 4.8; the overall model Performance of EfficientNetB7 without feature fusion

```
Accuracy: 0.8940493468795355
Precision: 0.9113636363636364
Recall: 0.8730043541364296
Specificity: 0.9150943396226415
F1-Score: 0.8917716827279466
```

Table 4.9; the overall model Performance of EfficientNetB7 using feature fusion

```
Accuracy: 0.9343251088534107
Precision: 0.9229681978798586
Recall: 0.9477503628447025
F1-Score: 0.9351951306838525
Specificity: 0.920899854862119
```

4.6 Skin Cancer Classification using Graphical User Interface (GUI)

A visually intuitive and user-friendly method of interacting with the classification system is provided by GUIs. Without requiring complicated command-line interfaces or programming knowledge, they offer buttons, menus, and graphical components that make it simpler for users—such as academics or healthcare professionals—to input data, set parameters, and carry out the classification process [88].

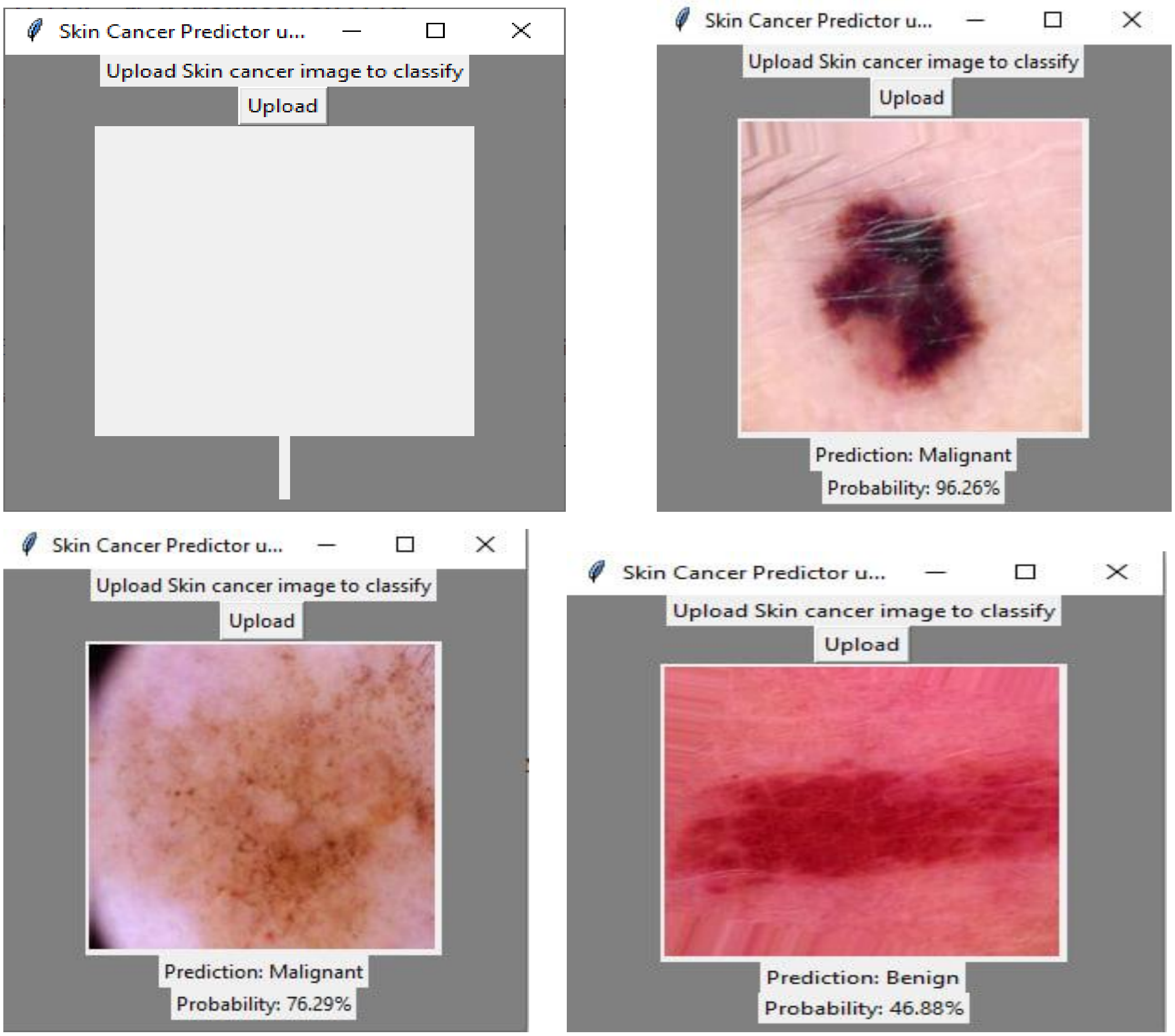

Figure 4.7; Classification of Skin cancer using GUI

4.7 Comparison Analysis with Other State-of-the-art Work

The results stated in Table 4.10, compare the proposed research work with other state-of-the-art done by different researchers in this area. The main aim of doing this analysis is to compare the model performance of the proposed method based on unseen datasets or test data with other existing work on particular diseases using several methodologies. The comparison criteria mentioned in Table 4.10, are based on similar class prediction, dataset type, and many different methodologies as well as the test accuracy regardless of the corresponding proposed work.

Table 4.10; Comparison analysis with the state-of-the-art research work

No	Work	Classes	Dataset	Methodology	Accuracy (%)
1	Pathiranage [42], 2017	Benign and Malignant	ISIC dataset with 2236 images	CNN	64
2	Kalouche [60], 2016	Benign and Malignant	ISIC dataset with 1280 images	VGG16	78
3	Mijwil [62], 2021	Benign and Malignant	ISIC dataset with 24,225 images	InceptionV3 ResNet VGG19	86.9 75.31 73.11
4	Bassel et al. [1], 2022	Benign and Malignant	ISIC dataset with 1000 images	Xception ResNet50 VGG16	90.9 81.6 87.5
5	The proposed work	Benign and Malignant	ISIC dataset with 27,560 images	EfficientNetB7 with a feature fusion strategy	**93.4**

4.8 Discussion

To address these issues and highlight obstacles and potential in this sector, this section discusses the challenges and opportunities for image classification in skin cancer disease. Our conclusions are based on the literature that has been evaluated as well as that in the related domains of computer vision, pattern recognition, and image categorization. Consideration of the same class category as benign and malignant and the use of dataset sources from ISIC allowed for a basic comparison between the proposed study results and the literature review. As mentioned in Table 4.10, in the work of Pathiranage [42], the author employs a CNN technique to classify skin cancer among two categories: benign and malignant, based on 2236 image datasets from ISIC. The overall test accuracy achieved was 64% which is very far from the results achieved by the proposed method. Similarly, Kalouche [60], obtained an average accuracy of 78% in VGG16 using 1280 skin cancer images from ISIC that are composed of benign and malignant skin cancer. Even if, the result achieved in this work is better than Pathiranage [42], but still a huge difference with the proposed study. Another study by Mijwil [62], stated three different deep learning models InceptionV3, ResNet, and VGG19. The author used a total dataset of 24,225 skin cancer images belonging to two classes (i.e. benign and malignant) and obtained the best accuracy of 86.9% in InceptionV3 when compared to ResNet and VGG19. On the other hand, Bassel et al. [1], Xception, ResNet50, and VGG16 are the three major models included. When compared to the other two methods, Xception yielded a far better result, with a 90.9% success rate. In general, the results stated in Table 4.10, confirmed that the proposed work outperformed by 29.4% of [42], 15.4% of [60], 6.5% of [62], and 2.5% of [1] in terms of test accuracy.

Even if the intended study produced considerable results, there is still potential for improvement. To address the data imbalance and improve model generalization, the study applied the data augmentation technique. As a result, it is advised that more skin lesions be collected for the categories with the fewest samples than for the other categories. Generally speaking, the proposed study model fuses different features to obtain higher accuracy and exceed the baseline study instead it can be used as an efficient tool for the detection and classification of skin cancer.

CHAPTER FIVE

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study established a system for classifying skin cancer lesions into two categories and classifying them using feature fusion on the EfficientNet algorithm, and transfer learning. The study specifically showed that dermoscopic image classification can benefit from pre-trained deep-learning models that were developed for natural image classification. However, it has been demonstrated that improving classification performance can be achieved by combining the detailed data from different network layers. The recommended model has the potential for use as a practical tool for medical practitioners to use in diagnosing skin cancer, according to the system's performance data. The study trained the EfficientNetB7 using the 27560 skin cancer datasets belonging to two classes benign and malignant by applying a feature fusion strategy to the pre-trained weight of an EfficientNetB7 and modifying the top classification layer. The Researcher looked at the evaluation metrics including Accuracy, Precision, Recall, Specificity, and F1- Score then achieved 93.4%, 92.3%, 94.8%, 93.5%, and 92.1% respectively as well as confusion matrix achieved 1269(92.00%) true positives, 109(8.00%) false positives, 72(5.00%) false negatives, and 1306(95.00%) true negatives. The use of a feature fusion strategy on a pre-trained EfficientNetB7 outperforms better accuracy of 93.4% compared to the existing research work. Furthermore, by using a larger dataset and implementing hybrid algorithm approaches with better performance, systems can be built into further study to identify and categorize the many types of skin cancer diagnosis of real-time skin lesions with advanced testing accuracy. In general, the proposed work will assist in reducing the delay associated with the diagnosis of skin cancer and help dermatologists to examine and categorize the class of skin cancer within a minute with more precision and decision-making as well as patient satisfaction also increase for being obtaining better services than the manual system that is time-consuming and a subjective judgment of the dermatologist which differ from one dermatologist to other based on the knowledge on identifying the exact type of the disease.

5.2 Recommendation and Future Work

The main objective of the health sector is working for the performance enhancement of disease diagnosis continuously until the highest accuracy level is reached as well as delivering effective or timely treatment and a well-organized recommendation system for the patients. There are several approaches to make the models perform better to achieve the promised performance. Being of excellent quality and clarity, dermoscopic images taken by physicians and dermatologists are not representative of the photographs taken by users, and the model was trained on them. Since user-submitted photos are generally of lower quality than those shot by professionals, the model would be more reliable if it were trained on them. Also, only photographs of persons with light skin were utilized to train both models. Therefore, lesions on darker skins have not been examined for performance. More information from different lesions on various complexions needs to be gathered to tackle this issue.

The proposed platform that integrates a feature fusion strategy on a pre-trained EfficientNet for skin cancer classification provides many valuable and remarkable directions in this area. However, there is also still a gap to be improved on the skin cancer classification in the deep learning techniques since the case is a serious Public health issue if left untreated in its early stage. As a result, there are some future work recommendations detected while implementing this research that need further investigation for better performance.

- ✓ Applying better fine-tuning techniques by unfreezing some layers to enhance the classification performance.
- ✓ Collecting huge labelled skin cancer data sets results in better classification accuracy.
- ✓ A model that includes a multiclass skin cancer classification and other skin diseases.
- ✓ In this research work the time consumption used for training the fused model is approximately 2 hours and 10 minutes, this time can be improved by using a GPU (Graphical Processing Unit) accelerator which is a powerful computing technique for training complex models.
- ✓ Developing an android application for addressing timely diagnosis and to make the patients as well the dermatologists user-friendly.

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