Jimma University

Jimma Institute of Technology

Faculty of Computing and Informatics

Hand Arthritis Disease Classification using Convolutional Neural Network

By

Bizunesh Mamo

Advisor: Dr. Worku Jifara (Ph.D.)

Co_ Advisor: Mizanu Zelalem (MSc)

Jimma University, Ethiopia

August 11, 2023

JIMMAUNIVERSITY

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

Information Technology Program

Master's Program in Information Technology (IT)

Hand Arthritis Disease Classification using Convolutional Neural Network

A Thesis Submitted To Jimma Institute Of Technology, Faculty Of Computing And Informatics In Partial Fulfillment Of The Requirements For The Degree Of Master Of Information Technology (IT)

BY: Bizunesh Mamo

Principal advisor: Dr. Worku Jifara (Ph.D.).

CO ADVISOR: Mizanu Zelalem (MSC).

August 11, 2023

JIMMA, ETHIOPIA

JIMMA UNIVERSITY

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF COMPUTING AND INFORMATICS

This Thesis work submitted to the School of Graduate Studies of Jimma University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Information Technology

Master's Thesis

Approval sheet

The undersigned certify that we have read and hereby recommend to the Faculty of Computing and Informatics, Information Technology program to accept the Document submitted by "Bizunesh Mamo" entitled "Hand Arthritis Disease Classification using Convolutional Neural Network" in partial fulfillment of the requirements for the award of a Master's Degree in (IT).

Hand Arthritis Disease Classification using Convolutional Neural Network

Submitted by:

Student Name: Bizunesh Mamo Signature ____ Date 27/06/2023

Approved by:

Main Advisor: Dr. Worku Jifara Signature ____ Date 27/06/2023

Co_ Advisor: Mr. Mizanu Zelalem Signature ____ Date 27/06/2023

External Examiner: Dr. Teklu Urgessa Signature ____ Date 27/06/2023

Internal Examiner: Getachew Mamo (Ph.D.) Signature ____ Date 27/06/2023

Chairman: Intelligent System Chair ____ Signature ____ Date 27/06/2023

Dean, Faculty of Computing and Informatics ____ Signature ____ Date27/06/2023

Director, Post graduate office ____ Signature ____ Date_27/06/2023

Acknowledgment

First of all, I would like to thank Almighty God and Saint Mary for helping me in my life. Next, I want to convey my sincere gratitude to Dr. Worku Jifara for all of his encouragement, support, and insightful criticism. Secondly, I'd want to thank my co-advisor, Mizanu Zelalem. I am incredibly appreciative of the time spent with me during these difficult moments, especially the painful nights of sadness and support, from all of my family and close friends. Without your assistance, I would not be here.

Contents

Approval sheet II

Acknowledgment III

Abbreviations VI

Abstract: VII

Chapter One: .... - 1 -

Introduction .... - 1 -

1.1 Background of the study .... - 1 -

1.2 Motivation .... - 3 -

1.3 Statement of the Problem .... - 4 -

1.4 Objectives .... - 5 -

1.4.1 General objective .... - 5 -

1.4.2 Specific Objectives .... - 5 -

1.5 Scope and limitations of the study .... - 5 -

1.6 Application of Results .... - 5 -

1.7 Ethical Consideration .... - 6 -

1.8 Organization of the Thesis Work .... - 6 -

Chapter Two: .... - 7 -

2. Literature Review .... - 7 -

2.1 Recent research about Arthritis Diseases .... - 7 -

2.2 What tests are conducted to diagnose arthritis disease? .... - 7 -

2.3 Arthritis disease Related works .... - 8 -

Chapter Three: .... - 13 -

PROPOSED HAND ARTHRITIS DISEASE CLASSIFICATION MODEL .... - 13 -

3.1 Research Design .... - 13 -

3.2 Ethical Consideration .... - 14 -

3.3 Data collection .... - 14 -

3.4 Data Processing and Analysis .... - 15 -

3.5 Research design and Method .... - 15 -

3.6 Digital Image processing in medical image analysis .... - 17 -

3.7 Image pre-processing .... - 17 -

3.5.1 Image Resize .... - 18 -

3.5.2 Feature Extraction ... - 18 -
3.8 Dataset preparation ... - 20 -
3.6.1 Image augmentation ... - 20 -
3.9 Classification ... - 22 -
3.10 Transfer learning ... - 23 -
3.11 Summary ... - 23 -
Chapter Four: ... - 24 -
4. IMPLIMANTATION OF THE PROPOSED DEEP LEARNING BASED HAND ARTHRITIS DISEASE CLASSIFICATION ... - 24 -
4.1 Introduction ... - 24 -
4.2 Experiment ... - 24 -
4.2.1 Implementation Tools ... - 24 -
4.2.2 Development Environment ... - 25 -
4.2.3 Convolutional Neural Network Parameters ... - 25 -
4.3 Model Building ... - 25 -
4.3.1 Model selection ... - 25 -
4.3.2 Dataset Preparations ... - 26 -
4.3.3 Model Evaluation and Analysis ... - 26 -
4.3.1 Parameters and Hyper Parameters in the model ... - 28 -
4.4 Results and Discussion ... - 29 -
Chapter five: Conclusion and future work ... - 40 -
5.1 Conclusion ... - 40 -
Thesis Work contribution ... - 40 -
5.2 Future Work ... - 41 -
References ... - 42 -

Abbreviations:

OA….osteoarthritis

RA…..Rheumatoid Arthritis

JRA …..Juvenile rheumatoid arthritis

IJSP…international journal of signal processing

ICCPCT…. International Conference on Circuits, Power and Computing Technologies

IP…image processing

PR….pattern recognition

SVN…. Support vector machine

CNN…..Convolutional neural network

GLCM…..Gray Level Co-Occurrence Matrix

DTCWT…..Dual tree complex wavelet transform

WHO… world health organization

RFC …… Random forest classifier

RGB------- Red Green and Blue

OPD -------- Outpatient department

Abstract:

The prevalence of arthritis is rising worldwide. Psoriatic arthritis, Rheumatoid arthritis and osteoarthritis are the most and frequently affecting arthritis joint chronic diseases. This arthritis disease causes pain, function limitation, and permanent joint damage in the hands and other joints of the body. Plain hand x-ray images are the most commonly used imaging methods for the diagnosis, differential diagnosis, and monitoring of arthritis disease. In this study, the convolutional neural network algorithm was used to obtain hand x-ray images, and classification was made by proposing hand arthritis CNN model. To investigate this research we use 1645 hand arthritis x-ray images in four classes. The data augmentation method was applied during the training of the network. We train 1645 hand x-ray image using 150x150 image size using 50 epoch. After we train, the result of the study were evaluated using deep learning evaluation metrics such as accuracy, sensitivity, specificity, and precision calculated from the confusion matrix of the model. In the classification of psoriatic arthritis, rheumatoid arthritis, *o*steoarthritis and normal hand x-ray image 91.4% accuracy, 83.2% sensitivity, x94.2% specificity, and 83.2% precision results are achieved respectively. In this study, to develop a computerized method, the CNN algorithm was used to classify the suspected hand x-ray images. In overall we explored the potential of computer aided image processing namely deep learning for hand arthritis detection and screening, and the findings shows that it might be used as a screening tool to classify hand Arthritis in low resource settings.

Keywords: Hand Arthritis classification, psoriatic arthritis, Rheumatoid arthritis, Osteoarthritis.

Chapter One:

Introduction

1.1 Background of the study

The word "arthritis" is a combination of Latin and Greek origin. Joint is denoted by "Arthron" in Greek, and inflammation is denoted by "Itis" in Latin. Therefore, it is common knowledge that arthritis is a disorder brought on by inflamed joints. Inherently, arthritis is not a single disease but rather a group of related medical conditions [1]. The exact cause of the disease is still unknown [2].

Inflammation of the joints occurs when two or more bones connect together, causing tremors and pain. Excruciating pain, joint swellings, joint stiffness, and poor joint function are all symptoms of arthritis [3]. Healthy joints move naturally with the help of a slippery and smooth tissue called articular cartilage. The tissues absorb pressure and shock caused by motion and pressure due to extreme stress on the joints where bones meet. Arthritis is caused solely by the breakdown of cartilage in the joints. Arthritis can affect the lining of your joints as well as the cartilage, which is the smooth coating at the ends of your bones. [4] The cartilage ultimately breaks down, exposing the ends of your bones, which scrape against each other and wear away. You have a lot of joints on your hands. Hand arthritis causes discomfort, edema, stiffness, and deformity [5] [6]. As your arthritis worsens, you won't be able to do the things you used to be able to do with your hands [7]. Millions of people are suffering from arthritis in their hands and fingers [8].

There are different types of arthritis such as osteoarthritis, rheumatoid Arthritis, and psoriatic arthritis.

Osteoarthritis, sometimes known as "wear and tear" or "degenerative arthritis. “Arthritis is a frequent condition. It causes the cartilage (the smooth, cushion-like layer at the joint) to deteriorate, to break down and wear away at the ends of your bones) the ends of the bones then, brush together without protection, resulting in pain, stiffness, and a loss of movement in the long run the most prevalent site of osteoarthritis is the wrist [9], which is the joint at the base of your hand. Youngers' middle and top joints, as well as your thumb. Long-term Disease can cause bony lumps to grow in your figure joints [1] [9].

An inflammatory condition called rheumatoid arthritis causes the lining of the joints to swell, which results in pain, stiffness, and function loss. Because it is an autoimmune disease, your immune system attacks healthy body tissue. A joint's synovium is its lining. Your synovium releases a fluid (lubricant) that makes it possible for cartilage to slip easily against one another. Inflammation eventually causes the cartilage at the ends of bones to deteriorate, leading to the bone's final dissolution. The joints lose their shape and alignment when the tendons and ligaments that around the bone deteriorate and strain. Rheumatoid arthritis commonly impacts your wrists, hands, and fingers due to their small joints [10]. On both sides of your body, it frequently affects the same joints. For example, if arthritis affects one hand's finger joints, it's likely to impact the other hand's finger joints as well.

Psoriatic arthritis, also known as psoriasis-related arthritis, is a type of arthritis that affects the skin and joints and is connected to a number of other medical conditions. Up to 30% of people with psoriasis also suffer from the most prevalent concomitant condition, psoriatic arthritis [11].

Prevalence data on arthritis in Africa remain scarce. Available studies reporting on prevalence have a wide range of estimates partly due to methodological differences and geographic or regional variation. Disability due to musculoskeletal disorders has increased by 45% from 1990 to 2010 and osteoarthritis is listed as the fastest increasing major health condition and ranked second as cause of disability by World Health Organization (WHO) [8].

Radiography (RA) is one of the most important assays for monitoring the progression of rheumatoid joint inflammation in human bone joints, according to this study [3]. Recognizing the precise phase of RA is a tough task, since human capacities frequently limit the methods for doing so. The center for hand recognition is the convolutional neural network (CNN), which recognizes complex cases. Because the human cerebrum functions at a high level, CNN was designed to mimic its unpredictable capabilities by relying on organic neural-related organizations in people.

It was thus presented the convolutional neural network (CNN), which has the ability to naturally learn competence with the qualities of hand radiography and predict the class from a large amount of data. The researcher employs a dataset of 290 radiography images to organize the model, and this work shows that the proposed methodology rates hand X-rays with an accuracy of 94.46 percent. The network sensitivity was found to be 95% and the specificity was found to be 82% in the researchers' experiment. However, the study did not demonstrate true competence, because the categorization was based on a single label and a limited dataset.

To treat the patient from pain and control from further damage of joints and repair the damaged joint via surgery. A medical history, physical examination, and an x-ray of the affected joint are used by doctors to diagnose hand arthritis. A reduction of joint space and the growth of bone branches can be seen on the x-ray in the case of arthritis in the hand.

Health care services are unlike any other, it is a high-priority industry, and people want the best possible care and services, regardless of the cost. Even though it consumed a large portion of the budget, it didn’t meet the social expectation. Medical experts are usually the ones who interpret medical data. Subjectivity, image complexity, significant variations among interpreters, and weariness limit human image interpretation.

Therefore, there is a need for automation of the Arthritis identification and classification system to assist healthcare providers in identifying the disease and for clinical discussion making.

Now, in our research work, we had designed a model only for the main types of arthritis disease detection and classification model to classify the above-listed types of arthritis the using Convolutional neural network, and as we explore still, there is no research work conducted to identify and classify these listed above three arthritis diseases.

To this end, we proposed a novel automated hand arthritis classification system based on convolutional neural network to detect and classify a hand arthritis disease.

1.2 Motivation

Our motivational reason for developing this diagnosis model is to address the critical challenges of arthritis diagnosis technology. Globally it is estimated that there are approximately 35-70 million of individuals are suffering with Arthritis [11]. Because each types of Arthritis disease have similar features during x-ray examination processes and the physicians take a lot of time and care to accurately examine the disease because of similarity of the disease symptom. But this is a situation that radiologists and physicians face while assessing arthritic patient because the symptoms of each kind of arthritis are similar [9], and determining the cause takes time. We are very interested in solving those problems, and as a member of the academic staff and an educated scholar, we wish to contribute to this effort and establish a sound foundation for my future academic research. As a result, we are very interested in conducting this research.

1.3 Statement of the Problem

Arthritis is one of the most frequent health issues that people face all around the world [8]. A person suffering from arthritis faces a considerable risk of early impairment and joint abnormalities. The damage to the joints might be minimized by early diagnosis and treatment of Arthritis. Many therapeutic approaches are now widely available for the diagnosis of this disease. The analysis depends heavily on imaging of the damaged joints [8]. Arthritis is a condition in which one or more joints swell and become tender. The main symptoms of arthritis are joint pain and stiffness, which typically worsen with age [8]. The most common arthritis diseases types include osteoarthritis, rheumatoid arthritis and Psoriatic arthritis.

Now a days in Ethiopia, there is no clear figure of the patient's statistical Information but the issue is a series and affects many adults [7]and leads too many socio-economic problems [8].

The most commonly used method of identification and classification of Arthritis disease done by experienced health care providers by manually reading the x-ray images [12]. This method is time consuming, requires experienced professional, and prone to human errors.

Numerous studies have used image processing, machine learning, transfer learning, and deep learning techniques to identify the arthritis disease [10] [13] [14]. But those research works only focus on a specific arthritis disease such as Rheumatoid arthritis [10], Osteoarthritis [15] and both Rheumatoid and hand osteoarthritis [16] and also they use a small number of dataset size up to 290 images [2], these 290 images may not give all the features of the diseases.

Therefore, in this study we proposed an automated deep learning based system to detect and classifies multiple arthritis diseases (Osteoarthritis, Rheumatoid arthritis and Psoriatic arthritis) from hand x-ray images. The most fundamental question we address in this research is as follows:

- How to develop an automatic hand arthritis classifier deep learning model?
- How to improve the performance of the developed deep learning models with other pre-trained CNN models?
- To compare the proposed model performance with the other pre-trained CNN model performance?

- To what extent the proposed model correctly classifies arthritis from hand x-ray image?

1.4 Objectives

1.4.1 General objective

The main objective of this study is to use a convolutional neural network model to identify and categorize hand arthritis.

1.4.2 Specific Objectives

- To address the general objective the following specific objectives were designed.
- To Review the literature for past studies that used image processing and deep learning approaches to classify arthritis.
- To collect the x-ray image dataset that enables us to train the model developed.
- To prepare the dataset by performing various image pre-processes techniques.
- To train the prepared dataset using the proposed CNN model to classify the hand arthritis.
- To train the prepared dataset using the ResNet50 and VGG19 pre-trained CNN model to compare with the proposed model classification performance.
- To evaluate the performance of the trained model using evaluation metrics

1.5 Scope and limitations of the study

The scope of this research work focusses only the most common happened hand arthritis disease. Namely osteoarthritis, rheumatoid arthritis and Psoriatic arthritis. And also we only take as assumption the data sets are collected from already suspected patients by physicians. And as a limitation we cannot include all types of hand arthritis.

1.6 Application of Results

As we know, there are many modern diseases diagnosis and support technology's available in the today's world. Healthcare cost has threatened many countries' financial health, and the effort needed to care for their nation, and it is the description of once country development status. The economic development of the country is highly related to healthcare status on once country nation. Therefore, to overcome the above-stated issue improving healthcare facilities and giving accurate diagnosis methodology for the patient is critical issue. The disease of Arthritis requires quality healthcare service, professionals and accurate diagnosis tools due to the nature of the disease. This is why we develop this diagnosis model. So, the beneficiaries of the research works are all stockholders of the community including Patients, Physicians (Radiologists, Doctors, nurses...), Patient families, community, and Researchers who also got the academic reward.

1.7 Ethical Consideration

The patient's information and x-ray image's confidentiality were guaranteed throughout the data collecting, preparation, and analysis phases as well as throughout the interviews with subject-matter experts (physicians). All medical data were safeguarded and used specifically for this research. We have Ethical approval letter from Jimma university ethical review board for the legality of the research proposal.

1.8 Organization of the Thesis Work

Here in this section we describes the organization of the paper structure. Next to this section the remaining paper part is organized as follows: Chapter 2 reviews related work of the disease of Arthritis and past study's, In Chapter 3, we describe the methodologies and algorithms of the proposed model work Chapter 4, Model development and result discussion: In this chapter, we conduct an experiment and apply analysis techniques stated under chapter 3, the dataset used, tool installation of the tool. Chapter 5, in this chapter, we briefly state the conclusion and future works of this research for future researchers.

Chapter Two:

2. Literature Review

2.1 Recent research about Arthritis Diseases

In this chapter, we describe the disease of arthritis and their diagnosis mechanism. As we introduce above the thesis organization structure in chapter two we try to review recent arthritis disease research work and technological diagnosis mechanisms from scientific perspective. It has been shown that 3.6 million people (15%), including 17.9% women and 12.1% men, suffer from arthritis. In addition, 12.7% of patients with rheumatoid arthritis, 32.1% with an undetermined form of arthritis, and 62% of patients with arthritis had osteoarthritis. A seventh of Australians suffer from arthritis. Age-related increases in arthritis prevalence largely impact females (ABS, 2017). Additionally, patients with rheumatoid arthritis (RA) have a greater mortality risk compared to the general population [17]. In addition, we visit many resource materials and websites, individual professional medical blogs also included in this chapter like books, scientific published research and conference papers and bibliography of the Arthritis disease affected community reports also reviewed. Additionally, the arthritis disease and medical imaging technology's contribution and their diagnosis and detection accuracy, as well as classification of each Arthritis disease, have been also reviewed. Finally, we compare and contrast related research works in the diagnosis of Arthritis disease accuracy with their algorithms, methods as well as the size of datasets used in their study. Because, our research work is conducted in image processing deep learning.

2.2 What tests are conducted to diagnose arthritis disease?

. There are numerous imaging techniques available to diagnose arthritic disease that enable a doctor to evaluate the internal structure of the body without performing an invasive surgery. Imaging procedures are frequently used to diagnose arthritis and assess how well a patient is responding to treatment. A diagnostic imaging procedure for arthritis can assist in identifying joint and bone abnormalities that might be symptoms of the disease. Among the several imaging techniques, x-ray imaging is one of the most popular. It is a radiology technique that produces pictures of the body's internal organs using a safe and low dose of radiation. An x-ray/

radiograph is used to test, to evaluate, diagnose and monitor degenerative arthritis, inflammatory arthritis and other chronic diseases condition. An x-ray can show how much the bones interacts at the joint point and are a useful tool to determine the amount of cartilage at the bones' point. An x-ray can also help to detect underlying conditions or deformities that may increase your risk of developing arthritis in the future [18].The reason why we choose x-ray image is from Many medical imaging procedures CT, PET-CT, MRI, X-rays, Ultrasound, Diagnostic Biopsy, Mammography and Spectrograph are the most used imaging and exploratory investigations in the process of image interpretation are x-ray images look bellow image [19].

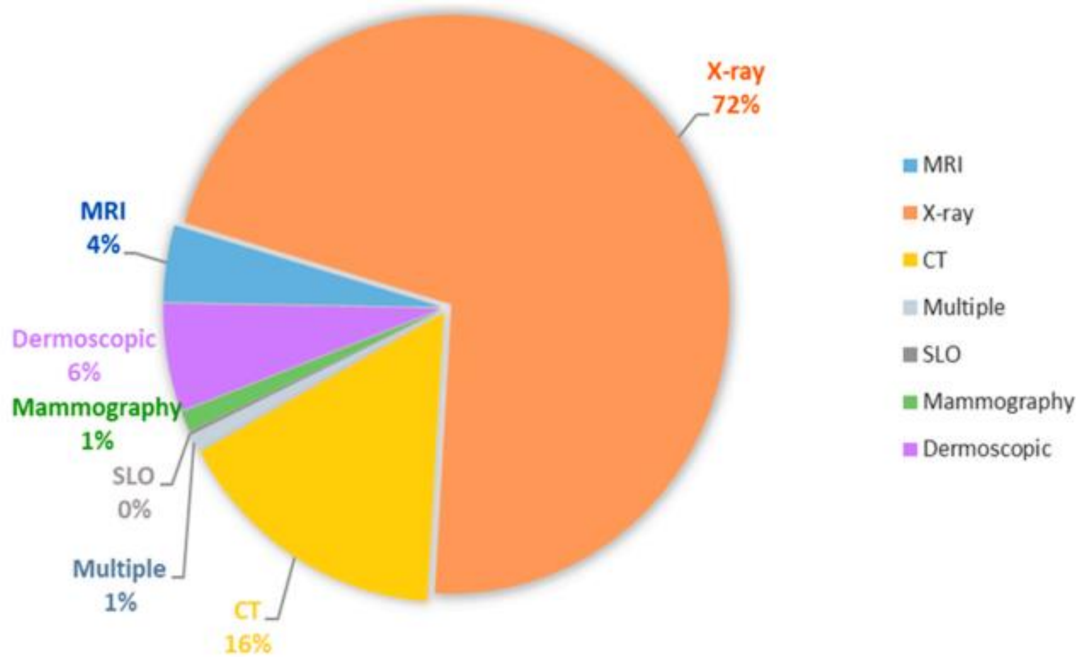

Figure 2.1: Medical procedure percentage [19]

2.3 Arthritis disease Related works

As the severity of the problem of an arthritis diagnosis, scientists conduct different research works to solve this problem, however still as we explore the biggest challenge which is classifying different types of arthritis disease is not yet solved. But some scientific research has been made to classify the level of arthritis disease and the presence and absence of the disease from the human joint is performed or solved using different machine learning algorithms. But now the time is deep learning and many problems are solved using this deep learning algorithm.

Some of the recent research works about arthritis disease is as follows. Efficient CNN deep learning model to classify hand x-ray images of Rheumatoid Arthritis, in this paper the author uses 290 hand x-ray images in two classes as normal and abnormal and the author achieves 94.5% accuracy of performance [20]. Knee arthritis Classification model to classify major frequent attack diseases with an accuracy of 91%, however, the author uses a small number of dataset 665x-ray images and in the clinical decision support system it needs high performance [21].

By applied the combination of FCN and CNN where FCN was used for Knee Detection, and CNN was used for both classification (0, 1, 2, 3, 4) and regression (0 to 4) tasks to predict the KL grade severity. The classification results are compared with Wndchrm, and this model trained from scratch outperformed Wndchrm with accuracy of 60.3% and MSE 0.898. Even the results are better than their previously reported methods that used BVLC CaffeNet for classifying Knee OA X-rays through transfer learning. These improvements are because of the lightweight architecture of the network with less (5.4 million) parameters compared to 62 million parameters of BVLC. When the network is jointly trained for classification and regression of knee images, the learning curves show a decrease in training and validation losses, and also an increase in training and validation ac-curacies over the training. In addition, an improvement in the multi-class classification accuracy was observed for network jointly trained for classification and regression as compared to the previous method. The confusion matrix indicated that the classification of Knee OA images conditioned on KL grade 1 was problematic be-cause of small variations [22].

However, the study only included 159 instances in total, of which 30 were used to verify the Deep Convolutional Neural Network. Instead, it employed hand radiographs chosen by expert radiologists. the discovery of three different synovial subgroups based on RA patients' synovial gene signatures. With the use of these labels, a histologic scoring algorithm was designed, and the histologic scores were then associated with several clinical indicators such the ESR and Creactive Protein level. The authors chose the 500 most variable expressed genes in 45 synovial samples (from 39 RA and six OA patients) and 14 histologic features from 129 synovial samples (123 RA and six OA patients). K-means clustering, in which n items are divided into k groups, with each object belonging to the cluster with the closest mean, was used to investigate geneexpression-driven subgrouping. Principal component analysis was used to validate this subgrouping because clustering was most resilient at 3 but not in a separate sample. Based on their gene patterns and enriched ontologies, three categories, including high inflammatory, low inflammatory, and mixed subtypes, were identified. The study's objective was to identify the relationship between synovial histologic characteristics and genetic subtype, resulting in a practical histology-based method for characterizing synovial tissue. A leave-one-out cross-validation SVM classifier was used to achieve this goal. Finding a decision hyperplane (i.e., the maximum distance to the closest training data points) that divides data points of distinct classes with a maximum margin is the goal of an SVM. The model did a reasonably excellent job of distinguishing between the high and low inflammatory subtypes and the other subtypes, but because their assessment dataset was so limited, the SVM over fitted [23]

The research conducted by [24] used fully convolutional networks [22]. The size of the input image was selected as 200×300 in order to preserve the aspect ratio on the basis of mean aspect ratio (1.6) for all the extracted regions of interest. They used Knee X-ray images and graded the severity level of the impairments according to the Kellgren and Lawrence criteria (an ordinal scale of five points). Elastic Net (EN) and Random Forest (RF) approaches were used to build predictive models using patients' clinical assessment data. X-ray images were used to train a convolutional neural network. Linear mixed-effect (LMM) models have been used to construct the relation between the two knees. For the CNN, EN and RF models, the root mean square error was 0.77, 0.97 and 0.94, respectively. Overall, the LMM reveals close predictive accuracy to the EN regression. However, this multi-stage pipeline approach, which ex-tracts and crops knee joints from the x-ray image requires a lot of memory [24]. As the Horlick features retrieved from ROI were one-dimensional data and insufficient for the proper classification, the Author employed SVM with fused kernel functions to categorise 130 radiographic pictures (30 normal and 100 pathological). Thus, to effectively classify the one-dimensional data, higher-dimensional data were mapped using kernel functions (such as linear, polynomial, and radial basis) [25]. As a reduction in space denotes OA, the KL grading system was utilised to evaluate Articular Space (AS) between bones. Additionally, only cases falling under grades 0, 1, and 2 were taken into account; all other cases were disregarded because joint space narrowing could be predicted with ease without the aid of any supporting tools. SVM classifier employed hyperplane classification to separate characteristics taken from knee joint ROI into normal AS and pathological AS joints during classification. The results showed that using RBF kernel functions led to better categorization outcomes. Furthermore, by combining extracted features and cascading kernel functions, the classification accuracy was increased [25].

In another work [26] developed a machine vision technique combining an active shape model and region-based analysis to diagnose knee OA. The histogram of oriented gradient (HOG) approach is used in the feature computation. Utilising a multiclass SVM classifier, the computed gradients are categorized in order to assess the OA based on the Kellgren Lawrence grading system. There are 616 computationally intensive inference algorithms in the dataset. Fully convolutional networks get rid of this bottleneck and produce excellent region recommendations, which rapid R-CNNs then use for object detection. The network has 101 layers, and in order to prevent overfitting, batch normalization and ReLU activation layers are placed after each convolutional layer. Additionally, the shared convolutional feature maps produced by the convolutional and max-pooling layers, which are employed by RPN and Fast R-CNN, abstract features. These feature maps are used as an input by RPN and as an output in the form of region suggestions. After computing the RPN inferencing scores and coordinates for each region, non-maximal suppression (NMS) is used to eliminate redundancy from the detection process. The anchor box with the greatest RPN score was preserved after applying NMS. They were able to create a complete deep learning model for the diagnosis of knee osteoarthritis using their suggested methodology [26]. The Author [27] scored knee severity using the KL grading scale using convolutional Siamese neural networks. The study employs the fine-tuned ResNet-34 as a baseline and presents novelties like developing a fresh strategy that makes use of Siamese networks to cut down on the learnable parameters and lessen the model's sensitivity to noise. The MOST and OAI datasets' radiographs might be used in the investigation. However, only the MOST dataset's 5, 10, and 15 degree beam angle photos were used. Instead of learning images using a similarity measure between the pairs, the study used image symmetry, and the network was able to learn the same weights for image sides. The Siamese network could reduce the number of parameters that needed to be learned. This made it simpler for the model to focus just on features that a human expert would take into account. The model achieved an AUC of 93% and a multiclass accuracy of 66.71% on the OAI dataset. The test set's qualitative analysis, however, revealed that the fine-tuned model can detect pointless or irrelevant elements. Additionally, GradCAM was used in the study to ensure that the model was detecting the appropriate features. The ability to reproduce the model and the results using the same dataset and implementation (code) is one of this method's greatest benefits [27].

Chapter Three:

PROPOSED HAND ARTHRITIS DISEASE CLASSIFICATION MODEL

3.1 Research Design

The experimental research design will be used. Because, experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand causal process. It is used for the researcher's for identifying cause and observes which powerful tool the diagnostic of the results is. In this study the researcher will be used experimental method for model building, analysis, and prototype development and testing, so, in our research we apply experimental research design. Experimental research is a scientific method of investigation in which one or more independent variables are altered and applied to one or more dependent variables to determine their impact on the latter. The influence of independent factors on dependent variables is frequently observed and documented over time to help researchers come to a plausible conclusion about the link between these two types of variables [28]. Experimental methods are a collection of skills and procedures for reducing measurement error and presenting results. The significance of effectively expressing experimental results to readers is an underappreciated part of experimental research. What will be released about an experiment can be influenced by how it is conducted, and vice versa is true of the other way around. Both directions on a two-way street are equally significant [29]. In our situation, we run trials to see whether an image is correctly classified or not. Therefore, in our situation, we try numerous experiments for each variable, such as altering the architecture of Convolutional neural network models, recording the outcomes or performances of these outcomes, and then performing yet another experiment till we obtained effective performance results by comparing the first one. The physical sciences, social sciences, education, and psychology frequently use experimental research design. It is used to hazard assumptions and draw conclusions about a subject. The first use of experimental research is in the field of medicine. Experimental research is employed to effectively treat diseases. Instead of using patients as research subjects directly, researchers most often take a sample of the bacterium from the patient's body and treat it with the developed antibacterial medication [28].

3.2Ethical Consideration

The Research and Ethical Review Board (RERB/IRB) of Jimma University have provide an approval letter of ethical clearance. In order to maintain confidentiality, names and addresses of professionals (experts) will not be recorded during the preparation or collection of data samples, and the x-ray images will only be used for research purposes.

3.3 Data collection

The data we make use of in our research is composed of up of hand x-ray images or x-ray image data. Because videos and images are the primary means of information delivery. The digital information communication in medicine (DICOM) file format will be used to save the photos. After we use various image preparation techniques, the obtained images can be stored in the computer and processed in actual utilizing deep learning algorithms. These image databases are the result of an X-ray taken of a real patient that was processed applying review by subject-matter experts. (Radiologists). We select Bilack lion Hospital because of the diseases difficulty to treat most infected individual patients are treated from this hospital from September 2020 to September 2022, we collect 1645 hand x-ray images from Tikur Anbesa (Black Lion) Hospital in four categories.

A)　　　　　　　　B)　　　　　　　　C)

Figure 3.1 Sample Arthritis Affected x-ray image(A: OA,B:PA, and C: RA)

3.4 Data Processing and Analysis

Once the data is collected, it is was processed by in steps called preprocessing, dimensionality reduction, color uniformity and classification using python as main programming Language in google colab jupyter notebook environment. Preprocessing will be done to enhance and remove noises from the image and to extract essential information for further image analysis. It includes Blur and focus corrections, Enhancements, Lighting corrections, filtering, noise removal, thresholding. Edge sharpening, and noise suppression. The main purpose of preprocessing is to converting DICOM file (default extension for x-ray images) to common image file (JPG) in the lossless way and enhance the quality of the images. Thus, the quality of the preprocessing has a large influence on the performance of the subsequent procedures. Before feeding the data to the neural network, dataset split will be done for training and testing. Split data into train: test randomly; well-known rule of splitting the data is 80–20 percent training and testing sets respectively. A training set will be used to train the network while a validation set will be used to monitor the model performance during the training process, to fine tune hyper-parameters.

3.5 Research design and Method

This study follows an experimental research design. Experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand the causal process. An experimental research design includes dataset preparation, implementation, performance evaluation, a designing hand arthritis diseases classification model. To detect and classify hand arthritis disease from hand x-ray images, it is important to follow a series of image processing steps. Figure 3.1 depicts the details of these steps. In this thesis, we follow the image processing concepts to customize the model for hand arthritis disease x-ray images detection and classification model. Accordingly, image analysis and understanding are used to classify hand arthritis disease into four classes RA, OA, PA, and Normal hand.

In this thesis we follow the following research design methods like data collection, data preprocessing , model training, classification ,and finally analysis of the model. The following two diagram is describing how the research work is conducted.

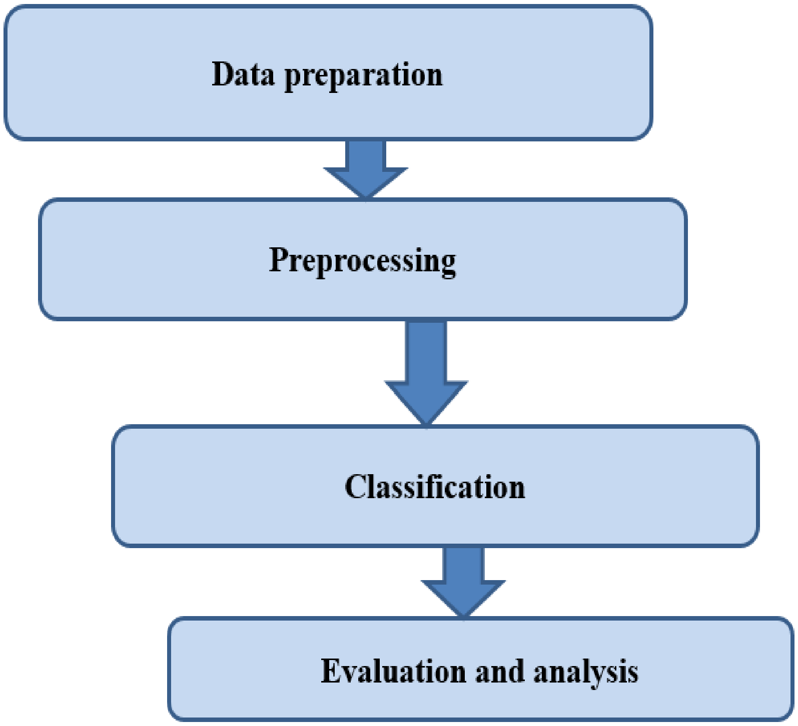

Figure 3.1: General Diagram of the Methods

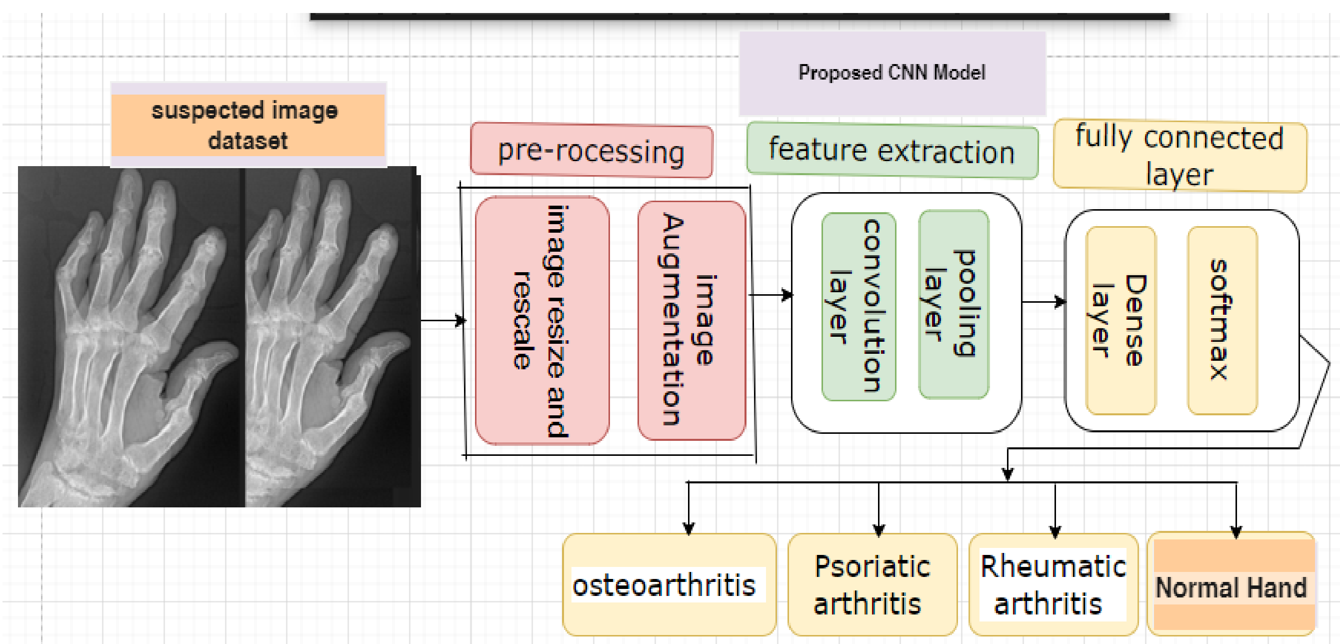

Figure 3.2: design of the proposed model work flow

3.6 Digital Image processing in medical image analysis

As one of the most recent generations of AI innovations, deep learning (DL) has embraced quick advancements in the early detection and classification of chronic-related diseases [30]. To apply this technology we need a large number of dataset. From this datasets image is the most fundamental source of medical image analysis. The definition of an image is a two-dimensional function, f (a, b), where a and b are coordinates in space or geographical coordinates in general. The intensity of the image at any given position is another name for the amplitude of f at any given pair of coordinates (a, b) [31]. An image is considered to be digital if its component discrete, finite quantities, a, b, and amplitude values are all present. A digital image is typically an array of numbers that depicts the spatial distribution of several appearance factors, such as temperature, emissivity, reflectivity of electromagnetic radiation, or some topographical or geophysical elevation. A digital image is composed of a finite number of elements, each of which has a particular location and value [31].

Pixels are the distinct visual components that make up a digital image. Each pixel has a number called a DN (Digital Number) that represents it. A DN value typically ranges from 0 to 255 in a scene's three elements or from 0 to 224-1 in a single numbering scheme. It represents the average brightness of a relatively tiny area inside the scene. The replication of details inside the scene is impacted by this area's size. More scene detail is kept in digital representation as the pixel size is decreased. Processing digital images using a digital computer is referred to as the field of digital image processing. Effective data capture and retrieval methods are used in digital image processing, including methodologies for sound image representation, display, pre-processing, and segmentation [31] .

3.7 Image pre-processing

Image processing is a method used to improve the quality of an image by removing irrelevant image data in a variety of applications and areas. There are many unwanted and undesirable components in the actual format of scanned medical images. For improved comprehension of the images prior to the discovery of the diseases in particular, some image preparation techniques are needed to get rid of such obtrusive components in an image [32]. CNNs require less preprocessing than conventional classification algorithms, which rely on manually created filters. CNN has the benefit of having learning filters that are independent of human involvement. The image preprocessing methods used in this study were normalization, color conversation, and image resizing. Image pre-processing is a technique of improving the quality of image by applying different techniques. Most of original medical images contain irrelevant portions that require pre-processing. To remove such irrelevant parts in the images, image preprocessing techniques are applied ahead of classification with the aim to enhance visualization of the images and improve performance of models [33]. Normalization, image color conversation and image resizing were specific techniques employed in this study. The original images were not uniform in size and they were resized into 50x50, 100x100 and 150X150 pixels. Feature extraction is a technique that changes the original feature of the data to a new smaller feature set that is more informative features. This smaller set of informative features is important for recognition to discriminate among different categories of classes. CNN is effective in extraction of deep features [34]. The powerful learning ability of deep CNN is primarily due to the use of multiple feature extraction stages that can automatically learn representations from the data [34].

3.5.1 Image Resize

Since the image's initial size wasn't constant, all subsequent iterations must be consistent in order for image preprocessing methods to adjust the image's pixel size to the appropriate value. This step is necessary if you need to increase or decrease the total pixel count for image standardization. Additionally, the image's reduction reduces processing expenses and time. Various sizes of images have been obtained. The first step in image preprocessing is to downsize the image since huge pixels require too much computational time and expense and the data set needs to be a similar size in order to employ the suggested approach. By resizing the dataset to 50x50, 100x100, and 150x150 pixels, we are able to evaluate three different image sizes in the model training phase to evaluate the nest image size to achieve best performance to classify the target classification problem.

3.5.2 Feature Extraction

To identify a descriptive feature on an x-ray of a hand with arthritis. Extracted features are typically descriptive and include features like texture features, color features, size features, and form features. In this work, the CNN feature extraction model was used. This is because image recognition and classification tasks currently use the CNN model, which represents the cutting edge. Due to its extensive use of feature extraction phases that may automatically learn representations from data, Deep CNN has excellent learning capabilities [35]. Convolutional neural networks are neural networks created specifically to analyze multi-dimensional data, such as image and time series data. (CNN). During the training phase, it includes feature extraction and weight calculation. By using a convolution operator, which is effective for handling complex tasks, the name of these networks is obtained. The key advantage of CNNs is automatic feature extraction, which is the real truth [36]. While current algorithms like CNN, DCNN, and VDCNN extract features automatically by learning thoroughly about the nature of data and which is an important component of data and which is not, older networks or classical machine learning features are created by a human being by hand or manually. In this study, the primary filter for extracting features or identifying patterns in the segmented image will be morphological (color, shapes, texture, and sharpness).

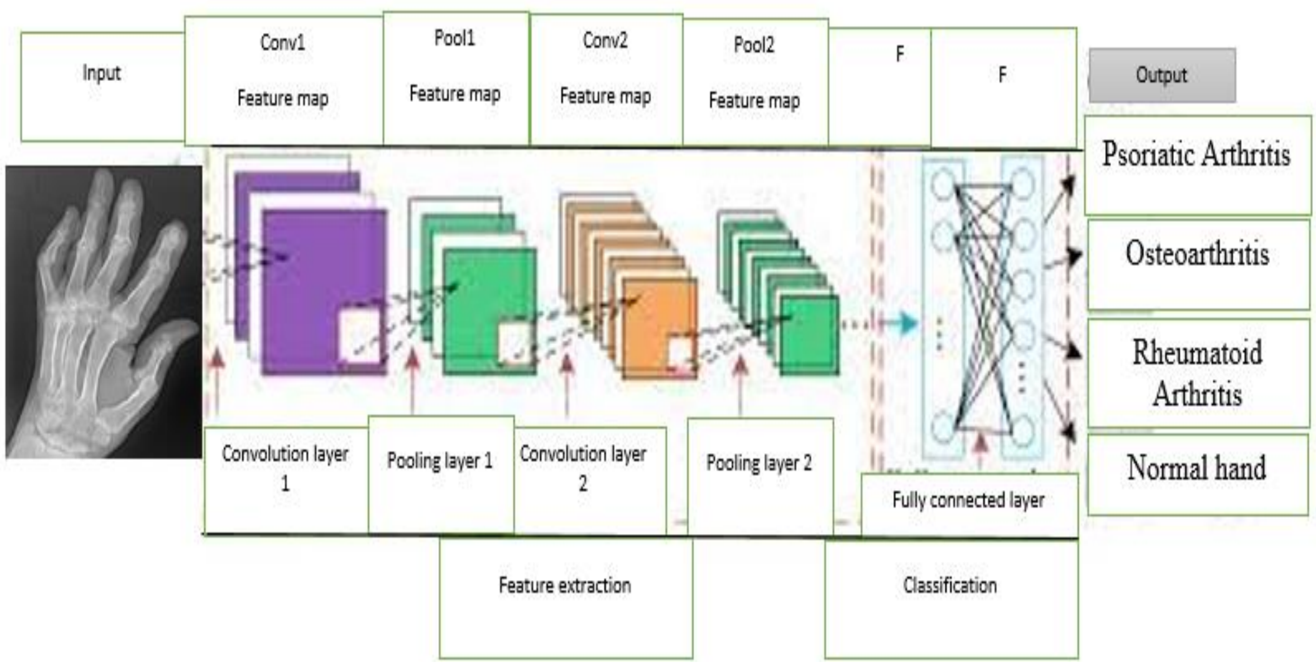

Figure 3.3 The Feature Extraction network

3.8 Dataset preparation

In the following table 3.1 we describe the dataset before and after augmentation.

Table: 3. 1 collected datasets for the work

Arthritis disease type	psoriatic Arthritis affected x-ray image	Normal hand x-ray image	Osteoarthritis affected x-ray image	Rheumatoid Arthritis affected x-ray image
Total number of x-ray images	387	463	426	369
Total dataset size:		1645 x-ray images		

3.6.1 Image augmentation

Deep learning often requires a large amount of dataset to train the neural network. Even if the collected dataset is so good to train the neural network but by increasing the collected image by augmenting the dataset we increase the datasets to train the neural network more effectively. It is a method for artificially expanding or growing the size of the training dataset. It is crucial since, in some cases, only a few number of training data samples are available for the majority of complicated real-world situations (such as medical datasets); nonetheless, more training data samples can lead to a CNN model with greater skill [37]. From many image augmentation techniques we apply rotation range, width_shift_range, height_shift_range, shear range, zoom_range,horizontal_flip, vertical flip. In this study, we augment 1040 images labeled into four classes: psoriatic Arthritis, Osteoarthritis, Rheumatoid arthritis and normal and x-ray. After augmentation, we have dataset of 5198 images as shown in Table 3.2. Image rotation is one of the most often employed augmentation techniques. The information on the image remains the same regardless of how it is rotated. Even if you look at it from a different perspective, the image remains the same. In order to increase the quantity of our training data, we may employ this method to create numerous image rotated at various angles. Image Shifting: Another technique of improving images is image augmentation. We can modify the position of the objects in the image by changing the images, giving the model additional variation. This could eventually lead to a more generic model. Image Flipping: Flipping can be considered as an extension of rotation. It allows us to flip the image in the Left-Right direction as well as the Up-Down direction.

```
datagen = ImageDataGenerator(
    rotation_range=0.45,
    width_shift_range=0.3,
    height_shift_range=0.3,
    shear_range=0.25,
    zoom_range=0.25,
    horizontal_flip=True,
  vertical_flip=True)
```

After applying all data augmentation techniques, Working with imbalanced datasets is a difficulty because most deep learning approaches neglect the minority class, which results in poor performance even though this performance is often the most crucial. One strategy for handling unbalanced datasets is to oversample the minority class. The simplest approach is to replicate samples from the minority class, however the instances don't reveal anything novel about the model. Instead, it is possible to construct new instances by synthesizing the existing ones. The Synthetic Minority Oversampling Technique, or SMOTE for short, is a type of data augmentation for the minority class. We add Oversampling techniques', which is a data science technique that duplicates samples from a minority class to create an evenly distributed dataset [38]. This is used to balance the class distribution of each class dataset size in the training dataset.

Table 3.2. Augmented dataset class distribution:

Arthritis disease type	**psoriatic Arthritis**	**Normal hand**	**Osteoarthritis**	**Rheumatoid Arthritis**
Number of x-ray images	**2709**	**3241**	**2982**	2583
Total dataset after augmentation	11,515			

3.9 Classification

The last step in this work is classification. In this thesis, CNN is the choice intended for this. Convolutional Neural Networks (CNN) are a specific type of neural network used in machine learning that are exclusively used to analyze array data, such as images. These networks are frequently employed in machine-learning based on machine learning that are specifically aimed at medical images [47].In this paper, we discuss a technique for creating a classification model for hand arthritis disease based on CNN. The learning model, which is built utilizing the training and validation phases, is used to do classification. As a result, the classifier receives its input from the features that CNN has extracted. Now, Softmax is the most popular classifier in CNN models. Softmax is used to categorize each image (in the testing dataset) into a particular or preset class by drawing on the information from the learning model as (Psoriatic arthritis, Rheumatic arthritis, Osteoarthritis, and normal hand). Convolutional Neural Networks (CNN), a kind of deep learning classifier, are utilized to categories real-time images in natural situations. It is difficult to identify medical chronic diseases medical images due to the wide variations in their shape, size, texture, color, background, arrangement, and imaging illumination. Due to their superior feature extraction abilities, CNN-based classification networks have grown to be the most popular pattern for categorizing chronic diseases. In the CNN classification network, the complete connection layer (or average pooling layer) + softmax structure is typically used after the cascaded convolution layer+pooling layer component. The majority of the networks now in use for categorizing chronic diseases use well-known network architectures for computer vision, including AlexNet, GoogleLeNet, VGGNet, ResNet, InceptionV3, DenseNets, and MobileNet. The process of predicting a certain class, or label, for something that is specified by a series of data points is known as image classification, and it is the final stage in the development of our model. For this assignment, we will utilize custom convolutional nueral network algorithm. After the network has been trained on the collected features, it will categories the images with their category.

3.10 Transfer learning

Transfer learning is the reuse of a pre-trained model on a new problem. It's currently very popular in deep learning because it can train deep neural networks with comparatively little data. This is very useful in the data science field since most real-world problems typically do not have millions of labeled data points to train such complex models. So, here in this research we apply transfer learning for the proposed problem above.

3.11 Summary

This chapter we had covers Hand Arthritis Diseases Classification model using convolutional neural Network algorithm for identifying and categorizing human hand arthritis diseases. Preprocessing, feature extraction, data augmentation, and classification are examples of model components that are presented.

Chapter Four:

4. IMPLIMANTATION OF THE PROPOSED DEEP LEARNING BASED HAND ARTHRITIS DISEASE CLASSIFICATION

4.1 Introduction

This section includes thorough details of the dataset utilized and the methods used to apply the selected CNN algorithm models. The following sections provide information on the methodology, dataset preparation, experimental results, and assessment measures.

4.2 Experiment

4.2.1 Implementation Tools

The experimentation process is conducted using a TOSHIBA laptop Computer with Intel(R) Core(TM) i5-5200U CPU @ 2.20GHz Logical Processor speed and 8.00GB (RAM), 500GB hard disk capacity with windows 10 operating system. For image understanding, image preprocessing, image feature extraction, and image classification purposes, we chose the Python computer language to develop the hand arthritis disease classification model. This programming language includes sophisticated machine-learning algorithms for recognizing and analyzing images. Python was the programming language of choice for developing the algorithms. The main factors that led to its selection were the code's simplicity and readability.

- ✓ Tensor flow is also a free machine learning library used for mathematical operation.
- ✓ Keras library used to create layers in the CNN model
- ✓ Kernel Size: Filter size to generate feature maps.
- ✓ Padding: For keeping the size of output equal to the input of the next layer.
- ✓ Pooling Size: Down sampling size of the convolved result.
- ✓ Learning Rate: a positive fraction determining the step of learning of the network neurons
- ✓ Dropout: a mechanism of regularization of the training to overcome overfitting

4.2.2 Development Environment

Google Collaborator (Colab): Colab is a completely cloud-based, free Jupyter notebook environment. The notebooks you create can be simultaneously modified by your team members, exactly like you edit documents in Google Docs, and most significantly, it doesn't require any setup. Many well-known machine/ deep learning libraries are supported by Colab and are simple to load in your notebook.

4.2.3 Convolutional Neural Network Parameters

Kernel Size: Filter size to generate feature maps.

Padding: For keeping the size of output equal to the input of the next layer.

Pooling Size: Down sampling size of the convolved result.

Learning Rate: a positive fraction determining the step of learning of the network neurons.

Dropout: a mechanism of regularization of the training to overcome overfitting

4.3 Model Building

4.3.1 Model selection

To train hand arthritis disease classification model using CNN algorithm we chose two pre-trained CNN model Resnet50, and VGG19 model and one custom CNN proposed mode. This pre-trained convolutional neural network already trained on more than a million images from the ImageNet database. This pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. Now, in our thesis, we propose a model and compare with the above mentioned pre-trained modes based on the transfer learning model principle to train the proposed problem which is four class hand arthritis disease classification using x-ray images. By removing the outer fully connected layers of the pre-trained model and replace by our custom four class fully connected layer or output class having four classes.

4.3.2 Dataset Preparations

The data to conduct this research was collected from Tikur anbesa specialized hospital Addis Ababa. As Cleary stated the dataset description under chapter three section 3.3 above, we did different image processing steps starting from image extension uniformity, color uniformity, size uniformity, brightness uniformity, and the like activities to change the same similar properties of images. The details quantities and varieties of sample images used in our experimentation are summarized in the following table 4.1 bellow.

Table 4.1 dataset distribution

Arthritis disease type	**psoriatic Arthritis affected x-ray image**	**Normal hand x-ray image**	**Osteoarthritis affected x-ray image**	**Rheumatoid Arthritis affected x-ray image**
Total number of x-ray images	387	463	426	369
Total dataset size:		1645 x-ray images		

```
[70]
for i in ['PA', 'Normal_Hand', 'OA', 'RA']:
    print('Dataset size of {} images are: '.format(i)+str(len(os.listdir('/content/drive/MyDrive/Hand_x_ray_image_dataset/'+i+'/'))))

Dataset size of PA images are: 387
Dataset size of Normal_Hand images are: 463
Dataset size of OA images are: 426
Dataset size of RA images are: 369
```

4.3.3 Model Evaluation and Analysis

The model were trained on 80% of the data while 20% will be used for testing. The reason why we choice 80-20 principle is most state of the art uses this dataset splitting technique to train the neural network. The metrics will be used to evaluate the model in this classification task are accuracy of classification accuracy (CA), precision, Recall, and F1 score.

***Accuracy*: -** The model will be calculated as the percentage of correct prediction of the top class (the class having the highest probability as indicated by the CNN model) and the target class will be assigned by the author before-hand is the same. It will be represented by the below,

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Where, TP (True positive) represents the positive instances that are correctly classified as positive, TN (True Negative) represents the negative instance that is correctly classified as negative, FP (False positive) represents the negative instance that is wrongly classified as positive, FN (False Negative) represents the positive that is wrongly classified as negative.

Precision: - will be calculated as the fraction of true positives (TP) from the sum of the relevant classes, i.e. the sum of the true positives and the false positives. It will be represented by the following formula.

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

Recall: - will be calculated as the fraction of true positives from the sum of True positives and False Negatives. It can be represented by the below,

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

***F1 score*:-**will be used in this experiment as the dataset is imbalanced. F1 score is interpreted as the harmonic mean of precision and Recall. It will be represented by the below.

$$F1\ Score = \frac{2 * precsion * Recall}{Precisoin + Recall}$$

A confusion matrix: - is also an evaluation metric that will be used to describe the performance of a classification task. Precision, Recall, and Accuracy can all will be calculated with the help of a confusion matrix.

4.3.1 Parameters and Hyper Parameters in the model

Some hyper parameters that are used to train our model dictate the network structure to produce the best possible results. By selecting the batch size, those groupings of hyper parameters are established for the network based on several training data sets. These are the number of epochs, batch size, number of iterations, and number of batches to complete the dataset in one epoch. Epochs are the number of times the model reads the entire data set presented in the next table 4.2 below. Some hyper parameters, or variables, used in the model's training process decide the network structure for the best training outcome. Which are: How many times the model reads the entire data collection in an epoch. Even though it takes longer to compute and train the model, there are instances when simply increasing the number of epoch's yields better results. Batch Size: Using a moderate batch size to examine portions of the entire dataset at once results in a smoother learning process for the model. The learning rate, which is a positive percentage, controls the network neurons' next stage of learning. Dropout: a training regularization strategy to combat overfitting

Table 4.2: Chosen CNN hyper-parameter Values

Hyper Parameter	**Value**
Activation	ReLu
Striding	2
Padding	Same
Kernel size	3x3
Batch size	32
Learning rate	0.0001
Dropout	0.5
Epoch	50
Optimizer	Adam

4.4 Results and Discussion

Reducing the image to its optimal size decreases processing time and cost. The dataset consists of images of different sizes. We resized images to the sizes of 150 x 150, 100 x 100, and 50 x 50. We carried out modeling by varying image sizes to obtain optimal performance. As the size of the image increases, it needs more computational time. The maximum accuracy obtained was with an image size of 150x150. These experiments have been discussed as follows: The first was done with an image size of 150 x 150. The training accuracy of the model has been 91.4% as shown the training and validation graph and confusion matrix of the model visualization in Figure 4.1 bellow.

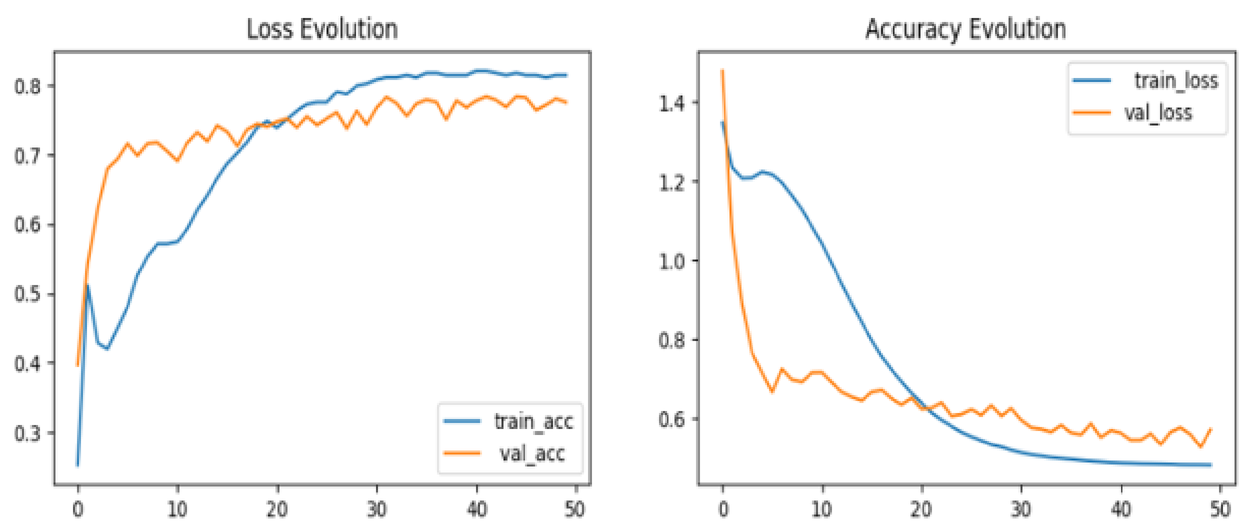

Figure 4.1 HandArthritismodel Training/Validation Accuracy and Loss for Image Size of 150 X 150

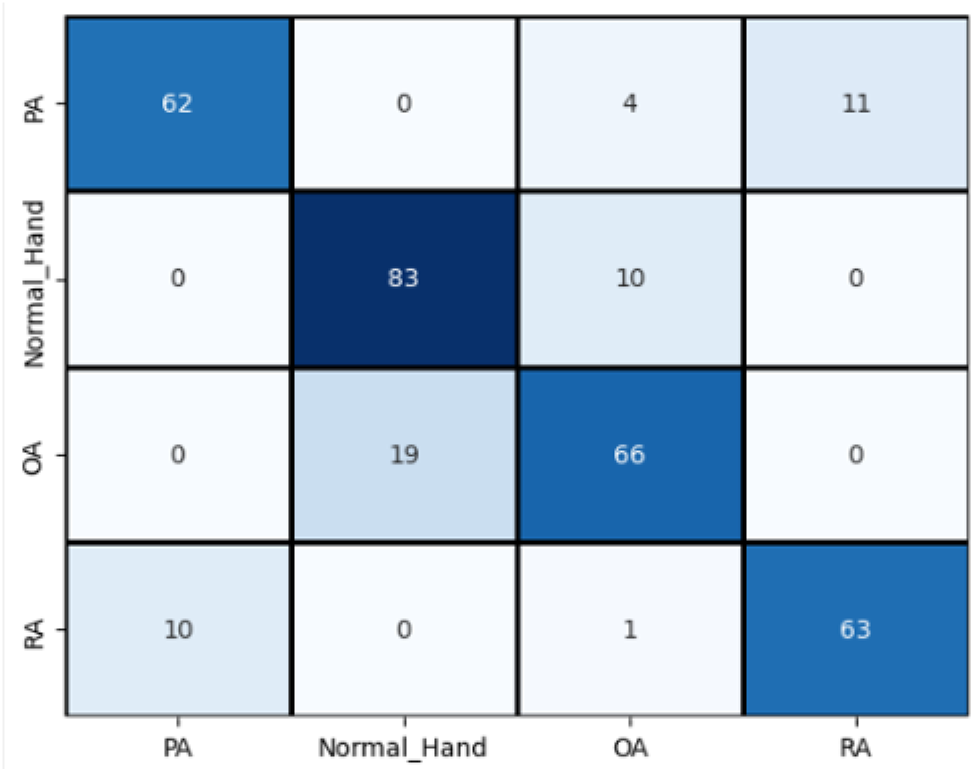

Figure 4.2 HandArthritismodel Image Size of 150 X 150 Confusion matrix

Table 4.2: HandArthritismodel Evaluation Result for Image Size of 150 X 150

Metric	**Value**
Accuracy	91.4%
Sensitivity/ recall	83.2%
Specificity	94.2%
Precision	83.2%
F1-score	83.2%

Then the next, modeling was done with an image size of 100 x 100. The training accuracy of the model has increased to 90.4% as shown the training and validation graph and confusion matrix of the model visualization in Figure 4.2 bellow.

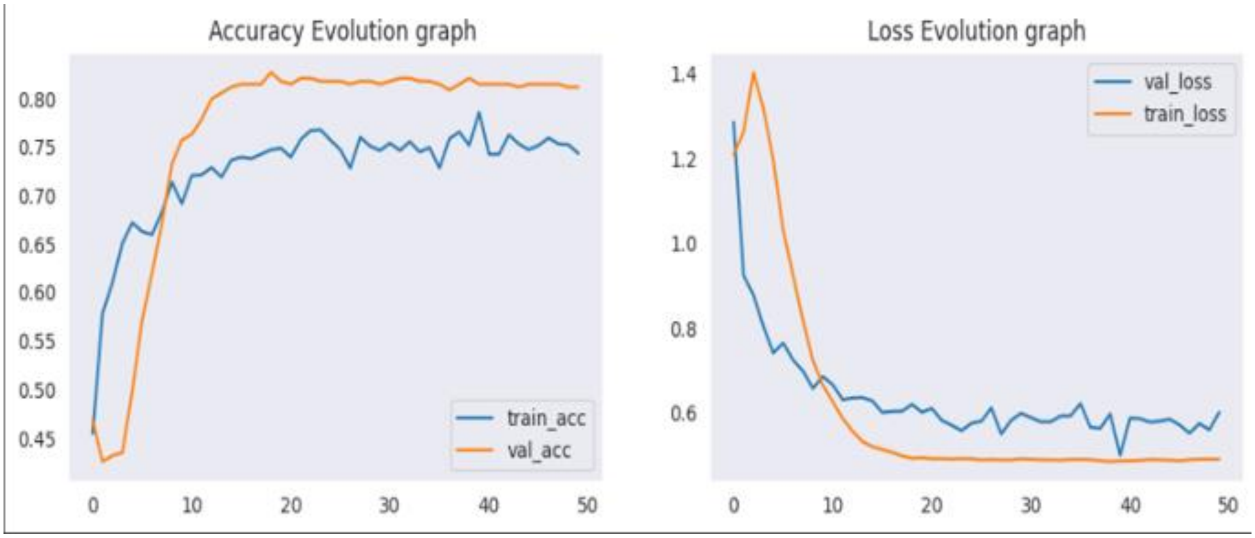

Figure 4.3 Training/Validation Accuracy and Loss for Image Size of 100 X 100

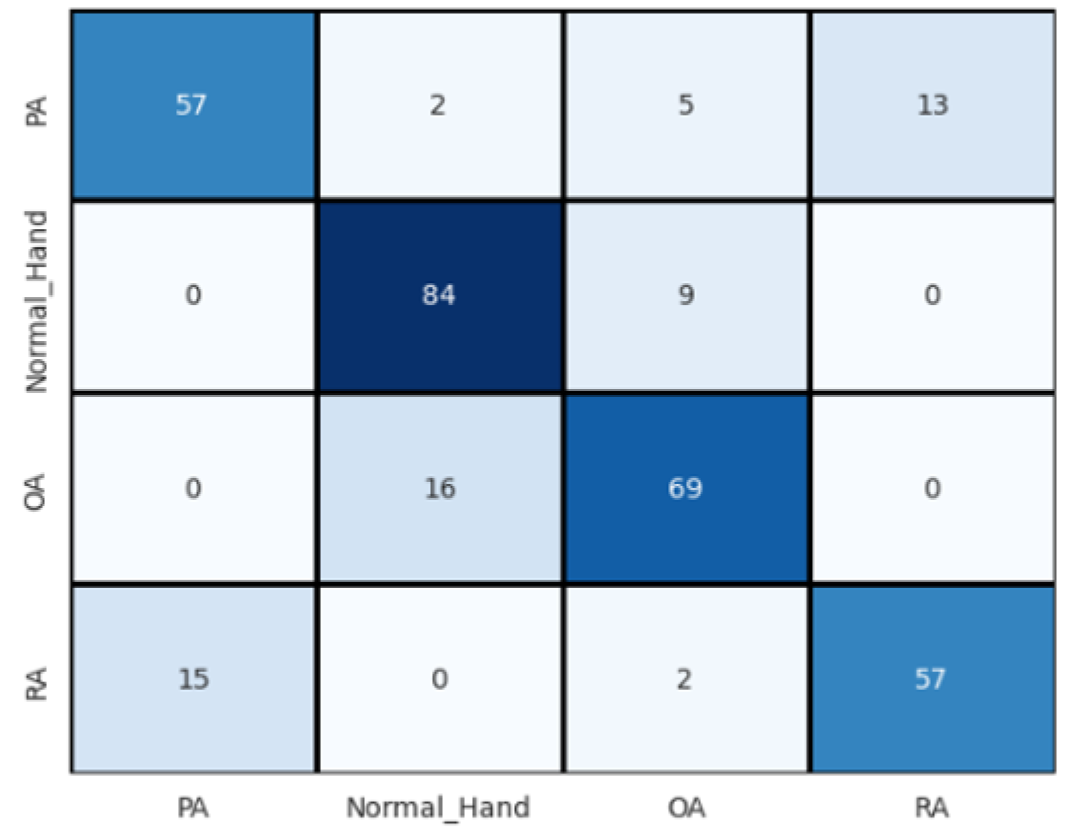

Figure 4.4 : Image Size of 100 X 100 Confusion matrix

Based on the above confusion matrix experimental result, we analysis the following evaluation metrics results indicated below table 4.3.

Metric	Value
Accuracy	90.4
Sensitivity/ recall	81.1
Specificity	93.6
Precision	81.1
F1-score	81.1

Lastly, we conduct the modeling was done with an image size of 50x50. The training accuracy of the model has been recorded 87.7%. The result showed that modeling with an image size of 150x150 has the best performance when compared with modeling with image sizes of the above three image size experiments and 100x100 and 50x50. The accuracy and loss and the confusion matrix of the mode are shown in Figure 4.3 bellow.

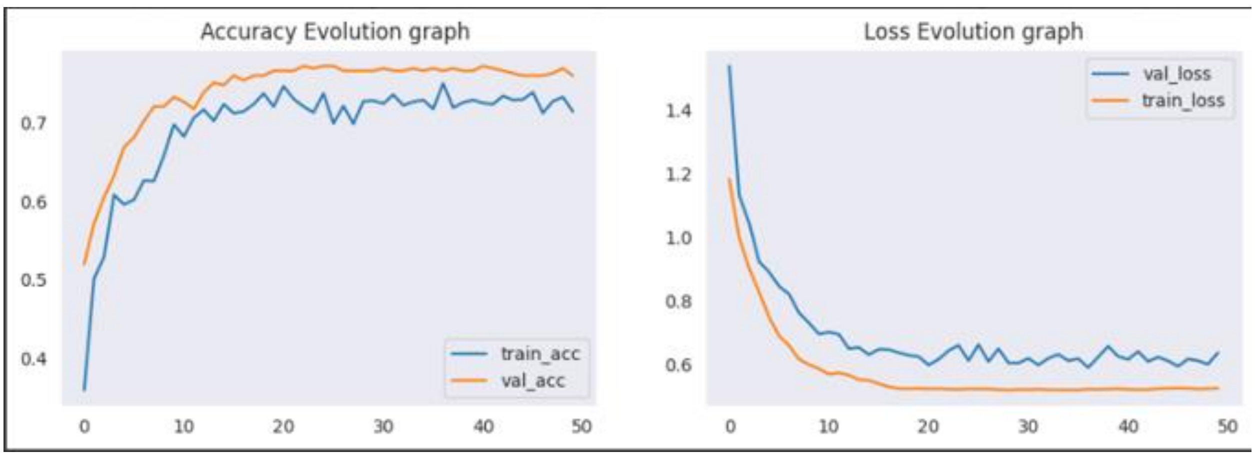

Figure 4.4: Accuracy and Loss for 50x50 Image Size accuracy and validation graph

Figure 4.5: Image Size 50x50 confusion matric

The modeling confusion matrix with an image size of 150x150 is shown in Figure 4.1 B. From the total of **329** validation images, **274** have been correctly classified and 55 incorrectly classified. As shown in Table 4.2 above, the performance of the model is an accuracy of 91.4%, specificity of 94.2%, a sensitivity of 83.2%, a precision of 83.2%, a recall of 83.2%, and an F1-score of 83.2%.

Table 1: HandArthritismodel Evaluation Result for image size 50x50 with ReLu activation function

Metric	**Value**
Accuracy	87.7
Sensitivity/ recall	75.9
Specificity	91.7
Precision	75.9
F1-score	75.9

Hyperparameter optimization is an important task to obtain optimal performance. We have conducted modeling with two activation functions: ReLU and ELU, separately to obtain optimal performance. The image size was 150x150. We conduct an experiment with image size 150x150 and an ELU activation function. The training accuracy of the model is 87.3 %, as shown in Figure 4.4 bellow. This shows using ReLu activation function outperforms best performance of the model.

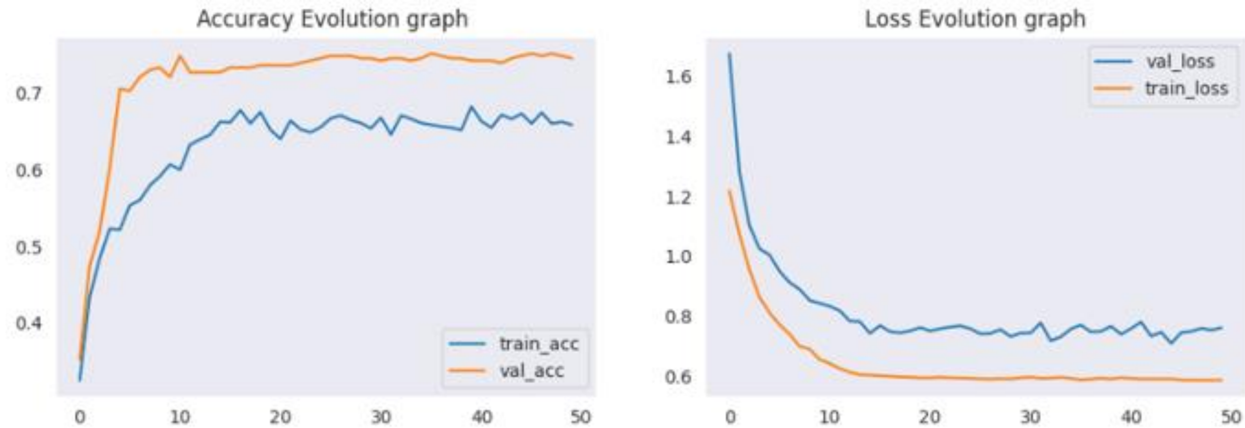

Figure 4.6: Training/Validation Accuracy and Loss with Elu Activation

Figure 4.7: Hand Arthritis image size 150x150 elu activation function confusion matrix Confusion matrix

The model was trained using 150x150 pixels of image size, and ReLU as an activation function. The training accuracy of the model has been 91.4%. This result shows that using the ReLU activation function enhanced the performance.

Table 4.5: HandArthritismodel Evaluation Result for image size 50x50 with elu activation function

Metric	**Value**
Accuracy	87.3%
Sensitivity/ recall	74.4%
Specificity	91.5%
Precision	74.4%
F1-score	74.4%

Then the next experiment is comparison has been made with similar CNN architectures using the same dataset and parameters. There are different types of deep neural network models, from these models, we have selected ResNet50 and VGG19 to compare the proposed model.

The ResNet50 model was trained using the 150x150 image size and the ReLU activation function. The training accuracy of the model has been 89.9% as calculated by in Figure 4.5 B confusion matrix shown below.

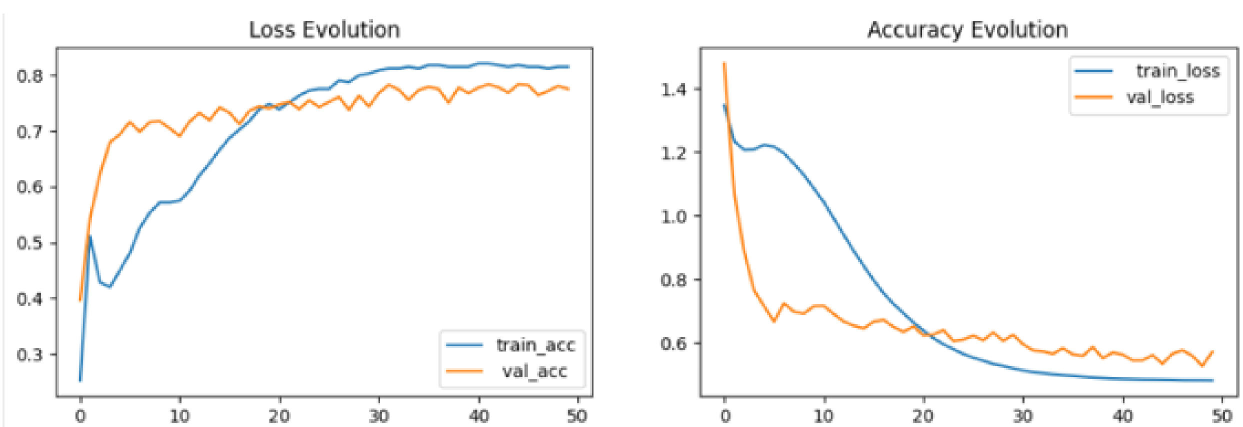

Figure 4.8: *Training/Validation Accuracy and Loss graph of ResNet50 model*

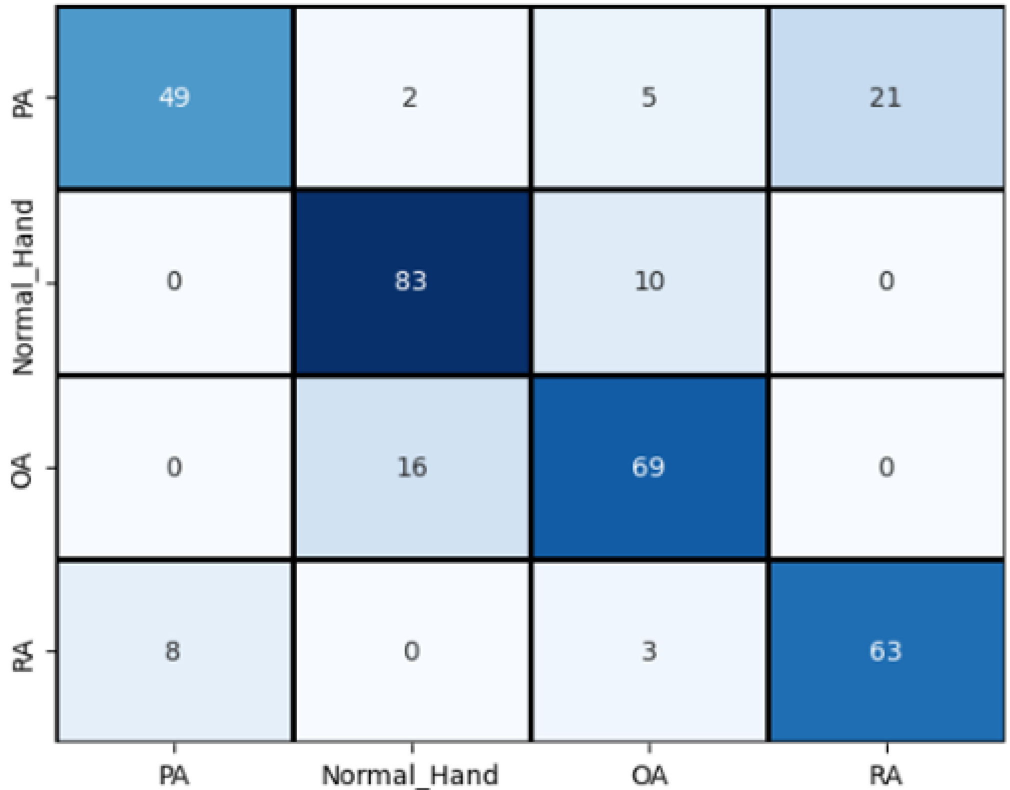

Figure 4.9: Confusion matrix of ResNet50 model

Table 4.6: HandArthritismodel Evaluation Result for image size 150x150 with ReLu activation function for ResNet50 pre-trained model result.

Metric	**Value**
Accuracy	89.9%
Sensitivity/ recall	80.2%
Specificity	93.1%
Precision	80.2%
F1-score	80.2%

Similarly the VGG19 model was trained using the 150x150 image size the ReLU activation function. The training accuracy and validation accuracy of the model has been 88.2% as calculated from model confusion matrix shown in Figure 4.9 below.

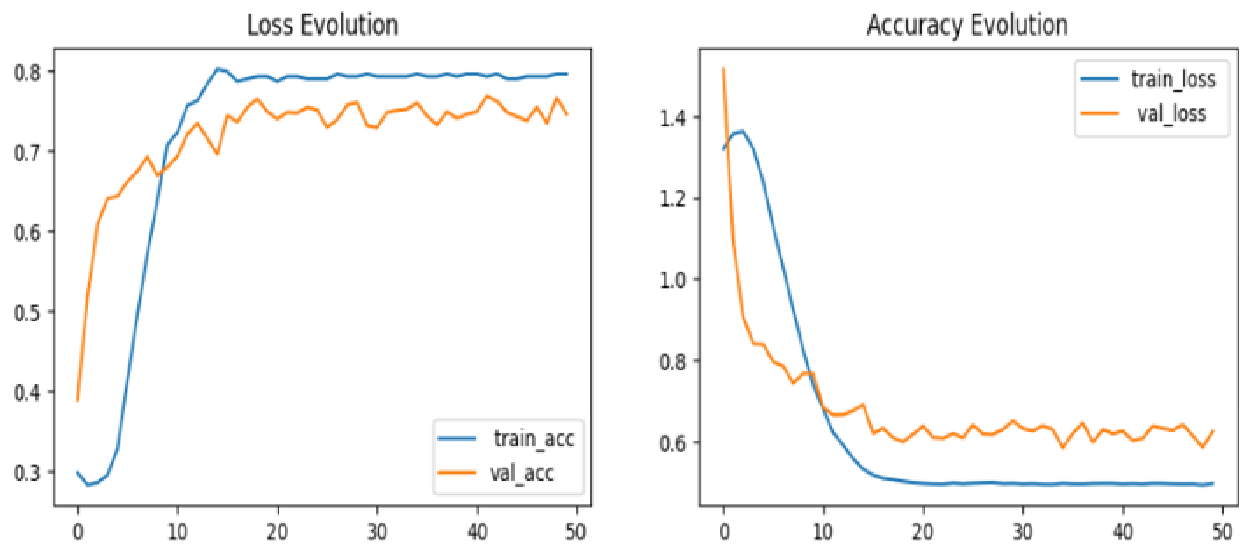

Figure 4.10: Training/Validation Accuracy and Loss of VGG19

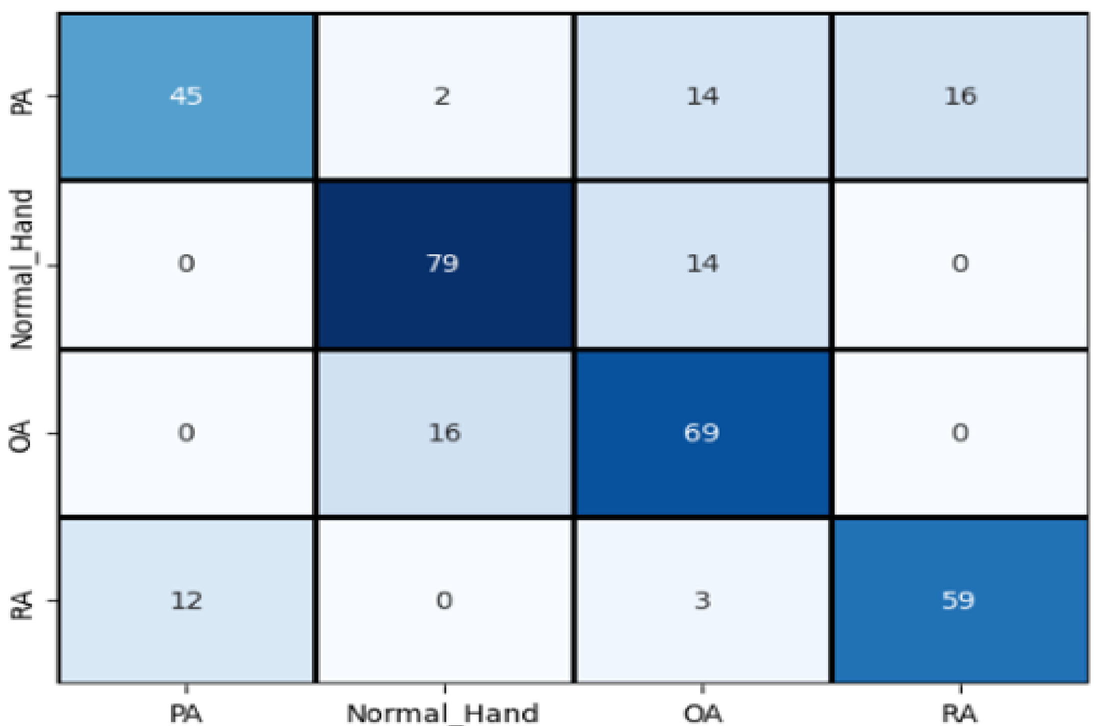

Figure 4.11: Confusion matrix of VGG19

Table 4.7: HandArthritismodel Evaluation Result for image size 150x150 with ReLu activation function for VGG19 pre-trained model result.

Metric	**Value**
Accuracy	88.2%
Sensitivity/ recall	88.2%
Specificity	92.1%
Precision	88.2%
F1-score	88.2%

In general, we conducted seven different experiments to achieve optimal performance and validate through comparison. These experiments were carried out to find an appropriate image size, activation function, and two pre-trained CNN models. The optimal result has been obtained with an image size of 150x150 and the ReLU activation function of the proposed HandArthritismodel model. The comparison with similar CNN architectures: ResNet50, and VGG19 showed that the proposed HandArthritismodel model significantly outperformed both of them. The stated results of the above conducted experiment have been shown in Table 4.8 below.

Table 4.8: Summary of Experimental Result

Model	Image size	Activation function	Accuracy Of the model	Correctly classified	Incorrectly classified
HandArthritismodel	50x50	ReLu	87.7	250	79
HandArthritismodel	100x100	ReLu	90.4	267	62
HandArthritismodel	150x150	ReLu	91.4	274	55
HandArthritismodel	150x150	Elu	87.	245	84
ResNet50	150x150	ReLu	89.9	264	65
VGG19	150x150	ReLu	88.2	252	77

Here we conclude that using ReLu activation function and 150x150 image size of the x-ray over performs an accuracy of 91.4% from all other experiments conducts with this scenario. So, the proposed model may help for health professionals in many aspects of this disease diagnosis. And also when we validate all models that we conduct in our experiment the proposed model with 150x150 image size with ReLu activation function outperforms more than the other and from 329 total images for validation the selected model correctly classifies 274 images. This shows the proposed model is best when we compare with other models.

Chapter five: Conclusion and future work

5.1 Conclusion

To summarize, this area represents a fresh study direction for addressing the challenging issues associated with internal medicine diagnosis. We are currently exploring novel ideas of diagnosis technology using deep learning approach image processing technique, with a focus on diagnosing hand Arthritis diseases, for which currently as we explore there is no written work. We prepare hand x-ray image dataset and we apply different image preprocessing techniques. Before augmentation, we use 1645 hand x-ray images and after augmentation we have 11,515 preprocessed images in total. At the time of data gathering, we consulted an experts in the area of radiologists and internal medicine specialists. The issue of many parallels between the various types of arthritis and their treatment requirements was resolved by this technological advancement. Utilizing hand x-ray images, we design a model specifically to diagnosis and classify hand arthritis diseases.

Now, using normal human hand x-ray images and the three most prevalent attacks of hand arthritis, this algorithm classifies the conditions. We experimented with three different x-ray image sizes to evaluate the model performance for each image size, as well as two pre-trained CNN models using transfer learning for developing this classifier model. These models are ResNet50 and Vgg16 with image size of 50x50, 100x100, and 150x150. From the experiment, we get an accuracy of 91.4% when using 150 x 150 image size and ReLu activation function. From this thesis work, numerous stockholders will be benefited from this study, but radiologists, physicians, and patients particularly benefit because it provides significant advantages in terms of time, appropriate medication, resources, and rapid disease recovery for patients.

Thesis Work contribution

In this research work, we contribute to the scientific community we develop a hand arthritis classification model to diagnose the disease, we make an important contribution to the health stack holders, from the nurse up to specialists, patients, and the patient's family and scientific community. And also we collect important datasets to the future researchers and also to implement into project based real-world application and to give the developed model service to the community

5.2 Future Work

We recommend for future researchers include their study of another arthritis type that is not included in our work. And can also develop another part of the body's parts those are may affected by arthritis disease like neck, elbow, knee and the like parts of arthritis diseases. In this this research work we consider, only four classes are taken into account. We advise adding more classes of disease to help differentiate between healthy hands and all prevalent hand arthritis diseases. And also by modifying the Hyperparameter and other variables in the training it may increase the performance of the model.

References

[1] S. P. Mitra, "ARTHRITIS: CLASSIFICATION, NATURE & CAUSE - A REVIEW.," *AJBBL ,* vol. 02, no. 03, pp. 01-19 , 2013.

[2] C. Clinic, Rheumatoid Arthritis, florado: a Cleveland Clinic medical professional , 2022.

[3] Hindawi, "An Efficient CNN for Hand X-Ray Classification of," *Journal of Healthcare Engineering,* vol. 2021, p. 10, 15 June 2021.

[4] a. C, Arthritis of the Hand, florida: a Cleveland Clinic medical professional, 2021.

[5] F. V. N. M. M. A. A. A. K. T. Farhad Akhbardeh, Classification and Assessment of Hand Arthritis, U.S.A: IEEE, 2019.

[6] M. Subramoniam, "Statistical feature based classification of arthritis in knee X-ray images using local binary pattern," *IEEE,* Vols. 20-21, no. 2, p. 189, 2013.

[7] a. C. Clinic, Arthritis of the Hand, florida: a Cleveland Clinic medical professional , 2021.

[8] V. K. Y. M. Anthony Usenbo, "Prevalence of Arthritis in Africa: A Systematic Review and Meta-Analysis," *PLOS ONE,* August 4, 2015.

[9] l. Rudford, Arthritis in Hands and Arthritis in Fingers. Rheumatoid Arthritis and Osteoarthritis Included. Symptoms, Signs, Treatment, Diet, How to Prevent & Exer, florada: Cleveland Clinic, 2013.

[10] 1. A. K. K. ,. a. B. K. S. 3. Gitanjali S. Mate, "An Efficient CNN for Hand X-Ray Classification of Rheumatoid Arthritis," *Journal of Healthcare Engineering,* vol. 2021, no. 5, p. 10, 15 June 2021.

[11] e. Bhupesh Kumar Singh, "An Efficient CNN for Hand X-Ray Classification of Rheumatoid Arthritis," *Journal of Healthcare Engineering,* vol. ID 6712785 , p. 10 page, 2021.

[12] S. C. A. C. S. H. Niall O’ Mahony, Deep Learning vs. Traditional Computer Vision, Ireland: IMaR Technology Gateway, Institute of Technology Tralee, Tralee, Ireland, 2021.

[13] 3. Jun-e Liu 1 and Feng-Ping An 2, "Image Classification Algorithm Based on Deep learning -kernel function," *Scientific Programming,* vol. 2020, no. 3, p. 14, 2020.

[14] 2. H. E. H. H. M. Kemal ÜRETEN1, "Detection of hand osteoarthritis from hand radiographs using convolutional," *Turkish Journal of Electrical Engineering & Computer Sciences,* vol. 2968 – 2978, no. 23, p. 2968 – 2978, 2020.

[15] 2. H. E. H. H. M. Kemal ÜRETEN1, "Detection of hand osteoarthritis from hand radiographs using convolutional," *Turkish Journal of Electrical Engineering & Computer*

Scienceshttp://journals.tubitak.gov.tr/elektrik/, vol. 28, no. 25.09.2020, p. 2968 – 2978, 2020.

[16] K. Ü. &. H. H. Maras, "Automated Classification of Rheumatoid Arthritis, Osteoarthritis, and Normal Hand Radiographs with Deep Learning Methods," *Journal of Digital Imaging. https://doi.org/10.1007/s10278-021-00564-w,* vol. 35, no. 2022, p. 193–199 , 2022.

[17] J. B. H. R. L. T. G. N. M. V. d. B. G. a. D. J. Van den Hoek, " Mortality in patients with rheumatoid arthritis: a 15-year prospective cohort study," *Rheumatology international,* pp. pp.487-493., 2017.

[18] E. radiology, "Envision radiology," [Online]. Available: https://www.envrad.com/imaging-tests-for-diagnosing-arthritis/. [Accessed 20 11 2022].

[19] a. Tudor Florin Ursuleanu et, "Deep Learning Application for Analyzing of Constituents and Their Correlations in the Interpretations of Medical Images," *MDPI,* vol. 11, no. 1373, pp. 2-48, 2021.

[20] e. Bhupesh Kumar Singh, "An Efficient CNN for Hand X-Ray Classification of rheumathoid arthritis," *Journal of Healthcare Engineering,* Vols. Volume 2021, Article ID 6712785, p. 10, 2021.

[21] T. Berihu Molla, "Developing And Investigation Knee Arthritis Classification Model From Knee X-Ray Image Using Deep Learning Approach," Jimma University, Jimma, 2021.

[22] K. M. K. M. N. E. O. Joseph Antony, "Automatic Detection of Knee Joints and Quantification of Knee Osteoarthritis Severity Using Convolutional Neural Networks," *Springer nature,* vol. Volume 10358, pp. ISBN : 978-3-319-62415-0, 2017.

[23] S. H. K. T. J. K. H. a. A. T. Murakami, "Automatic identification of bone erosions in rheumatoid arthritis from hand radiographs based on deep convolutional neural network. Multimedia Tools and Applications," *Multimedia Tools and Applications, ,* Vols. 77, , pp. pp.10921-10937., 2018.

[24] J. A. J. M. K. M. K. O. N. Abedin, "Predicting knee osteoarthritis severity: comparative modeling based on patient’s data and plain X-ray images," *Scientific reports, ,* pp. 9(1), p.5761., 2019.

[25] Subramoniam.M, "A non-invasive method for analysis of arthritis inflammations by using image segmentation algorithm," *International Conference on Circuits, Power and Computing Technologies [ICCPCT-2015] IEEE,* pp. (pp. 1-4), 2015, March..

[26] S. P. P. M. K. a. H. Gornale, "Determination of osteoarthritis using histogram of oriented gradients and multiclass SVM.," *International Journal of Image, Graphics and Signal Processing,* 2017.

[27] M. C. K. e. Li, "Siamese neural networks for continuous disease severity evaluation and change detection in medical imaging.," *NPJ digital medicine,* vol. 3, no. 1, p. p.48., 2020.

[28] formPlus. [Online]. Available: https://www.formpl.us/blog/experimental-research. [Accessed 30 03 2023].

[29] R. Maxion, "Experimental Methods for Computer Science Research," *Fourth Latin-American Symposium on Dependable Computing,* 2009.

[30] J. T. W. 1, "Role of Deep Learning in Predicting Aging-Related Diseases A Scoping Review," *MDPI cells ,* vol. 2924, p. 10 , 2021 .

[31] N. K. a. D. Kumar, "Classification using Artificial Neural Network Optimized with Bat Algorithm," *Int. J. Innov. Technol. Explor. Eng.,* vol. vol. 9 , no. no. 3, doi: 10.35940/ijitee.c8378.019320., pp. pp. 696–700,, 2020.

[32] S. a. T.Velmurugan, "Preprocessing by Contrast Enhancement," *International Journal of Pure and Applied Mathematics,* vol. 118, pp. 3681-3688, 2018.

[33] S. a. T.Velmurugan, "Preprocessing by Contrast Enhancement," *International Journal of Pure and Applied Mathematics,* vol. 118, pp. 3681-3688, 2018.

[34] 2. A. S. 2. U. Z. a. A. S. Q. Asifullah Khan1, "A Survey of the Recent Architectures of Deep Convolutional Neural Networks," *Published in Artificial Intelligence Review,* 2018.

[35] 2. A. S. 2. U. Z. a. A. S. Q. Asifullah Khan1, "A Survey of the Recent Architectures of Deep Convolutional Neural Networks," *Published in Artificial Intelligence Review,* 2018.

[36] P. i. T.M. Navamani ME, "Efficient Deep Learning Approaches for Health Informatics," in *Deep Learning and Parallel Computing Environment for Bioengineering Systems*, 2019.

[37] A. Ghosh.et.al, "Fundamental Concepts of convolutional Neural Network," in *In Recent Trends and Advances in Artificial Intelligence and Internet of Thing springer*, 2020, pp. 519-567.

[38] G. L. S. a. e. Mizanu Zelalem Degu, "Smartphone Based Detection and Classification of Poultry Diseases from Chicken Fecal Images Using Deep Learning Techniques," *Smart Agricultural Technology,* 2023.

[39] V. K. T. Y. A. M. Anthony Usenbo1, "Prevalence of Arthritis in Africa: A Systematic review," *PLOS ONE,* 2015.

[40] L. L. •. Y. Z. •. G. C. L. Yang, Deep Learning and Convolutional Neural Network For Medical Image Computing, Switzerland : springer, 2017.

[41] M. I. S. N. a. A. Z. Razzak, "Deep learning for medical image processing: Overview, challenges and the future," *Classification in BioApps,* pp. 323-350, 2018.