A ROBUST DEEP LEARNING APPROACH FOR KNEE OSTEOARTHRITIS DISEASE CLASSIFICATION

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

JULY 2024

APPROVAL

This Project titled **"A Robust Deep Learning Approach for knee Osteoarthritis Disease Classification."**, submitted by **Md. Abrar Farhan Fahim** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents.

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I hereby declare that, this project has been done by us under the supervision of **Dr. Md. Fizar Ahmed, Associate Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First, I express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

I really grateful and wish our profound our indebtedness to **Dr. Fizar Ahmed**, **Associate Professor**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Machine Learning (ML)*, *Image Processing*, *Deep learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express our heartiest gratitude to **Dr. Fizar Ahmed**, **Associate Professor**, **Dr. Sheikh Rashed Haider Noori, Head Department of CSE, Daffodil International University, Dhaka.,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

I would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

Knee osteoarthritis (KOA) is a primary cause of chronic pain and impairment that greatly reduces the quality of life for those who have it. Precise categorization of KOA is crucial for efficient diagnosis, formulation of treatment strategies, and tracking of the disease's advancement. leaf diseases can significantly impact tea crop productivity and quality, necessitating timely and accurate detection for effective management. KOA is a common ailment that progresses gradually and causes noticeable changes to the bone in X-ray images. Because they are affordable and simple to use, X-rays are the recommended diagnostic method. Physicians assess the severity of each KOA patient's disease using the Kellgren and Lawrence (KL) grading system. This method classifies the illness into stages ranging from mild to severe. Treatment can slow down knee degradation by using this method for early diagnosis. In this work, we combined two datasets to create a raw picture collection of 2042 images. To enhance image quality and generate a substantial dataset, we used image pre-processing techniques, such as resizing images and CLAHE. We employed a number of well-known algorithms (ResNet50, VGG19, InceptionV3, VGG16, and the suggested model) in our work to identify five different KOA illness classes (normal, doubtful, mild, moderate, and severe). In the end, the suggested model has the best accuracy (96.56%) when compared to other algorithms.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The most prevalent cause of disability worldwide is osteoarthritis (OA). People also refer to it as age-related arthritis, wear-and-tear arthritis, degenerative joint disease, and primary OA. Physicians use the word arthritis to describe inflammation of the joints. In the field of public health, we collectively refer to over 100 rheumatic illnesses and ailments affecting joints, surrounding tissues, and other connective tissue as arthritis. Knee osteoarthritis (KOA) is a degenerative joint condition that primarily affects the knee joint. According to Lespasio et al. [1], it is typified by the degeneration of cartilage in the knee, which results in discomfort, stiffness, and a restricted range of motion. KOA typically develops slowly over ten to fifteen years and interferes with day-to-day activities, affects the medial, lateral, and patellofemoral joints. It was once thought to be only the result of aging-related "wear-and-tear" of the articular cartilage condition, unrelated to inflammation. Despite the ongoing investigation and poor understanding of the illness's mechanism, the complex etiology of knee OA remains widely acknowledged. Among the many variables linked to knee OA are lower limb alignment, inflammation from metabolic syndromes, trauma, aging, obesity, diabetes, synovitis, innate immunity, systemic inflammatory mediators, and both biomechanical and inflammatory whole-organ disease processes. Furthermore, studies have shown that individuals who have undergone ACL injury and reconstruction are at a higher risk of developing radiographic knee osteoarthritis later in life [2]. These results suggest that early intervention, knee injury management, and the use of ACL injury prevention techniques may lower the risk of knee osteoarthritis and enhance the long-term quality of life associated with knees. Research indicates a significant association between symptomatic knee OA and factors such as knee trauma, injury, and physically demanding activities like kneeling, bending, squatting, and prolonged standing. Knee OA occurs more frequently than other forms of OA. Increased risk factors for knee OA include age, overall lifetime activity, and population weight averages, with obese women being particularly at risk. According to estimates from the World Health Organization (WHO), osteoarthritis affects 18.0% of women and 9.6% of men over 60. Twenty percent of them struggle with everyday duties, and eighty percent have mobility issues. A different research project predicts that the number of adults over 45 with KOA will increase by 15.7% by 2032 compared to 2013 [3]. Over 25% of individuals in Bangladesh over 60 have KOA, according to BHS (Bangladesh Health Statistics), which is consistent with worldwide trends. A ratio of 1.5 to 2:1 disproportionately impacts women compared to men [4]. The physical demands of agricultural employment lead to a 10%–15% higher prevalence of KOA in rural populations than in urban ones. Furthermore, obesity increases the risk significantly; 25–35% of obese people are more likely to have KOA [5]. These ratios demonstrate the importance of thorough epidemiological research in Bangladesh in order to understand and manage the disease's consequences. The etiology of a knee ailment might influence the symptoms that occur. The discomfort surrounding the knee joint is the most typical sign of osteoarthritis. Dull, acute, continuous, or intermittent (off and on) pain are all possible. The range of pain is minimal to excruciating. One can reduce the range of motion. The patient may experience muscular weakness and hear cracking or grinding noises. The knee giving way, swelling, and locking are frequent bothersome signs. These impairments, which are mostly pain-related, typically show up as challenges when walking, climbing stairs, doing housework, and sitting up straight. They also have a detrimental psychological effect and can lower one's quality of life. Knee pain can start suddenly or progress gradually over time (this is the most typical scenario). The most common times for pain and stiffness are in the morning, after sitting, or after extended rest. Over time, painful feelings may become more frequent, particularly at night or while you're sleeping. Usually, the pain increases with more strenuous activity. Gelling, the word for stiffness and soreness in the joints after prolonged sitting or relaxation, generally passes in less than 30 minutes [6]. Reviewing the various forms of KOA should come first in the diagnosis and categorization of knee OA. Historically, we have divided OA of the knee into two types: idiopathic (primary) and secondary, based on its origin. Knee idiopathic osteoarthritis (OA) is often localized, although it may become more widespread if it affects three or more joint sites. The primary joint's anatomic involvement is another way to categorize knee OA. Before the practitioner makes a clinical diagnosis of idiopathic knee OA, they should examine and rule out any secondary underlying illnesses. It is important to thoroughly evaluate any secondary knee problems that can increase the likelihood of developing knee OA [7]. There are several ways to categorize the phases of osteoarthritis, although radiographic results can correlate with multiple symptoms. The clinical presentation and radiological results may differ in an inexplicable way. Radiography is not as effective in detecting knee morphology as magnetic resonance imaging (MRI). It offers a comprehensive image of the knee's composition and structure, yet it costs more than radiography. Despite the promise of magnetic resonance imaging (MRI), the majority of orthopedic surgeons still use conventional weight-bearing radiography. Moreover, X-rays are widely accessible, reasonably priced, and safe. And aid in the detection of articular cartilage degradation, articular space narrowing between neighboring bones, and bone spur growth [8]. One well-liked categorization method is the Kellgren & Lawrance (KL) OA classification. By assessing osteoporotic formations, subchondral sclerosis, and joint space constriction, radiologists can determine the disease's severity and provide a score between 0 and 4. Specifically, it has been demonstrated that the joint knee space width (JSW) is essential for predicting the onset and severity of osteoarthritis. This knee JSW aids in forecasting how OA will advance [9]. To identify KOA Grades 0 to 4, a number of studies used various deep learning and machine learning techniques using x-ray imaging datasets. However, their model's multi-class classification accuracy was not up to par. Thus, correctly categorizing KOA phases from X-ray images remains a challenging, laborious, and error-prone process. Additionally, we suggested a methodology to determine the severity of knee OA. It would be very advantageous to increase the validity and repeatability of X-ray interpretation for OA diagnosis.

1.2 Motivation

There are numerous benefits and reasons to use image processing for KOA disease classification. KOA is still a serious worldwide health issue that requires prompt, correct detection and categorization in order to provide appropriate care. We strategically integrate transfer learning, a potent artificial intelligence approach, to leverage prior knowledge from unrelated tasks and improve the model's knee OA detection in medical images. The effectiveness of deep learning models in image processing further enhances the study's potential. The goal of this research goes beyond simply accurately identifying and categorizing KOA in comparison to other categorization methods. Gaining a thorough understanding of KOA's complexities and spatial scope necessitates an understanding of the subtleties of these techniques. The present work aims to improve the validity and repeatability of X-ray interpretation for OA diagnosis by introducing a model that integrates soft attention and LSTM model. The study's ultimate goal is to establish the groundwork for developments in knee OA diagnostics, providing a revolutionary improvement in the precision and effectiveness of the procedures involved in detection and classification. By improving our understanding of how to optimally employ soft attention and the LSTM model in this context, the research aims to make a significant contribution to both the academic discourse and the practical domain of healthcare. Better diagnostics can have a direct and positive impact on patient outcomes, as well as the public health landscape.

1.3 Research Objective

a) To accurately identify disease classes, investigate research gaps in the current deep-learning-based knee osteoarthritis disease classification techniques.
b) Collecting data from Kaggle and presenting a proposed model aims to outperform existing models in the classification o knee osteoarthritis diseases.
c) To use a variety of image pre-processing techniques to remove noise and improve image quality so that the model can predict the class more accurately.
d) To improve classification precision by utilizing a novel proposed deep learning approach.

1.4 Research Questions

The research questions for deep learning-based knee osteoarthritis disease classification, can be presented as follows:

- ➔ What are the most effective image processing techniques, such as CLAHE, histogram analysis, feature extraction, Segmentation techniques for accurate and reliable detection of knee osteoarthritis?
- ➔ How can we investigate the weaknesses in the current deep-learning-based algorithms that are able to correctly categorize various knee osteoarthritis disease classes?
- ➔ How can we improve the image processing algorithm's performance and accuracy in identifying disease, particularly in differentiating between different types of knee disease?
- ➔ What are the primary factors and parameters that influence the image processing method's effectiveness in classifying knee osteoarthritis, and how can we adjust them to achieve optimal results?
- ➔ What is the accuracy, efficiency, and practicality of the created deep learning algorithm in comparison to current techniques for knee osteoarthritis disease classification?

- ➔ What are the limitations and challenges associated with the deep learning-based algorithm for classifying knee osteoarthritis disease, and how can we address them to improve the system's overall functionality and applicability?

1.5 Report Layout

Chapter 1: Introduction

The first chapter introduces the research and discusses the relevance of knee osteoarthritis categorization and the use of deep learning techniques. It provides an overview of the study's objectives, research questions, and the overall framework of the study.

Chapter 2: Literature Review

Chapter 2, a comprehensive assessment of the research on knee osteoarthritis disease prediction is the main emphasis. It explores the methods, strategies, constraints, and findings of earlier research projects carried out by other researchers. The goal of the chapter is to provide a comprehensive understanding of the existing literature and point out any gaps that the current research is trying to fill.

Chapter 3: Research Methods

Chapter 3 presents and discusses the research methodologies used in the study in detail. This chapter covers the procedure for gathering pertinent data, including the sources and techniques utilized. This chapter also covers the pre-processing methods used for KOA disease categorization. It also provides a detailed description of the proposed model.

Chapter 4: Result and Discussion

Chapter 4 presents the primary research findings. This chapter presents the model's accuracy curve, as well as highlights the results and conclusions that came from their examination. The chapter provides a thorough summary of the results and their consequences, supporting the study's aims.

Chapter 5: Conclusion and Future Work

The last chapter, Chapter 5, thoroughly discusses the research and its conclusions. It offers a critical analysis of the study's shortcomings and offers suggestions for future lines of inquiry and advancement.

CHAPTER 2

Literature Review

2.1 Related Works

Numerous researchers have attempted to classify knee osteoarthritis disorders in the past using a range of techniques, but their efforts have proven unsuccessful. Since deep learning has been extremely prominent in the medical imaging field for classifying various illnesses and several health conditions, numerous researchers have been employing different deep learning algorithms to identify KOA disorders. Here are a few instances of relevant literature:

The Discriminative Shape-Texture Convolutional Neural Network (DST-CNN) is a method for early KOA detection using X-ray images that is presented by Nasser et al. [10]. This model employs a Gram Matrix Descriptor (GMD) block to assess texture and form features, as well as a novel discriminative loss to improve classification. Surprisingly, DST-CNN achieves excellent performance, with metrics such as 68.46% precision, 74.08% accuracy, and other strong figures. It surpasses previous CNN-based techniques in its ability to distinguish between healthy people and borderline cases. The study emphasizes how every component of DST-CNN increases its effectiveness, with the best results coming from combining different textural insights with discriminative loss at different phases. Given the modest variances in early-stage KOA X-ray pictures, this model strongly emphasizes enhanced texture analysis through the GMD block, a crucial improvement often overlooked in conventional CNN designs.

Furthermore, Guida et al. [11] suggested a combination model that improves the severity of KOA diagnosis by utilizing MRI, X-ray, and clinical data. Initially, a 3D model for MRI reached 54% accuracy, while a traditional CNN for X-rays got 50% accuracy. When combined with medical information, the accuracy increased to 62%. Training a new X-ray model on a larger dataset increased its accuracy to 70%. Combining this novel X-ray model with the MRI and clinical information further increased accuracy to 76%. This model achieved an AUC of 0.964, enhancing the categorization of OA and non-OA patients. Plans for the future include investigating the KL 1 grade's specific accuracy problem and exploring alternative MRI and X-ray models.

Olsson et al.'s [12] proposal involved using a large collection of unfiltered radiography knee tests and deep learning to automatically classify the severity of KOA in people. Based on the ResNet architecture, the researchers trained a 35-layer convolutional neural network (CNN) using 6103 manually annotated photos using the KL scale. After training for 100 epochs without noise interference and then 50 epochs with noise components added, the CNN demonstrated exceptional efficiency, with an AUC greater than 0.87 for the majority of KL grades. The study demonstrates CNN's accuracy in assessing the severity of knee OA even in the presence of contaminated data, highlighting both its competence and its promising potential for use in medical diagnostics.

In addition, Mohammed and his team [13] presents deep neural network (DNN) models in X-ray image detection and classification for KOA. Using three distinct datasets, the authors tested six pre-trained DNN models: VGG16, VGG19, ResNet101, MobileNetV2, InceptionResNetV2, and DenseNet121. They were able to get maximum classification accuracies of 69%, 83%, and 89%. Among these, the ResNet101 DNN model fared better.

However, Patron et al. [14] investigate the use of tibial spiking as a possible characteristic for KOA early detection. The scientists conducted studies to compare patients with and without tibial spiking, and they created a deep learning-based model for identifying tibial spiking from plain radiographs. According to the study, individuals with tibial spiking have more severe osteophyte scores in the lateral tibial compartment, medial joint space narrowing, and KL grade. The proposed method's accuracy of 0.869 suggests that it may be used to diagnose KOA. The study does, however, note many drawbacks, including the use of noisy KL values as ground truth for mode training and the absence of a generally accepted atlas for evaluating tibial spiking.

A. Qadir [15] presents an enhanced deep learning system that aims to identify and categorize the severity of KOA. It is based on a bidirectional long-short-term memory (BiLSTM) network. We train the model on the Mendeley VI dataset and cross-validate it on the Osteoarthritis Initiative (OAI) dataset. ResNet extracts features from segmented knee pictures. Notably, the method achieves testing accuracy of 84.09% and cross-validation accuracy of 78.57%. We use metrics such as accuracy, precision, recall, and F1 score for assessment. The system does an amazing job of classifying knee pictures with an overall accuracy of 84.09%, precision of 92.5%, recall of 99.11%, and F1 score of 95.69% into five categories: healthy, Phase I to IV. Notably, our method outperforms existing deep learning models in terms of resilience, accuracy, and testing and training times.

Chaugule et al. [16] introduced a Deep Convolutional Neural Network (DCNN) model that can effectively classify the severity of KOA using digital X-ray images. The model includes: There are four steps in the process: dividing the image into separate areas, extracting all features, autoencoder-driven denoising, and a feature fusion stage to make the representation better. We notably optimize the DCNN using the Adam method, achieving remarkable testing and validation accuracies of 96.31% and 95.70%, respectively.

2.2 Scope of the problem

Researchers have made several attempts over the years to use empirical methods to detect knee osteoarthritis disorders based on their shape and gap, but their efforts have not shown satisfactory results. Research has indicated that manually recognizing KOA from X-ray images can be a laborious operation with a significant chance of human error. Additionally, several researchers have looked at KOA identification using machine learning and deep learning techniques. They lacked the information required to accurately classify and diagnose the various types of osteoarthritis in the knee. But surprisingly, their accuracy rates have been rather low.

2.3 Challenges

Tea leaf disease detection using image processing poses several challenges that need to be addressed for accurate and reliable results. These challenges include:

- ➢ **Variation in Disease Symptoms:** There are five phases of progression for knee osteoarthritis (OA), ranging from mild symptoms to severe impairment. Understanding the knee gap from X-ray images and appropriately assessing these differences presents a problem since various classes may exhibit similar visual symptoms that might result in misclassification.

- **Image Processing:** The Images collected from different locations occasionally showed noisy images or contrast levels that were too high or low. Thus, the challenge is appropriately preparing noise-free, contrast-enhanced images for identification.

- **Select the Superior Deep Learning Method:** Many academics employ a variety of deep learning techniques to simplify their tasks. The goal is to select the most effective deep learning techniques that can accurately identify each type of knee osteoarthritis using a variety of deep learning models and a deep learning strategy.

- **Accuracy Improvement:** The difficult task is to improve the models' accuracy and select the best one.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Working Process

The total work is to be completed in several phases, which are as follows:

1. Data description
2. Data Pre-processing
3. Apply Algorithms for classification
4. Classify knee osteoarthritis (KOA)
5. Result Analysis

Figure 1 illustrates the detailed procedures from data assemblage to outcome scrutiny, and the next section will go into great detail explaining how it works.

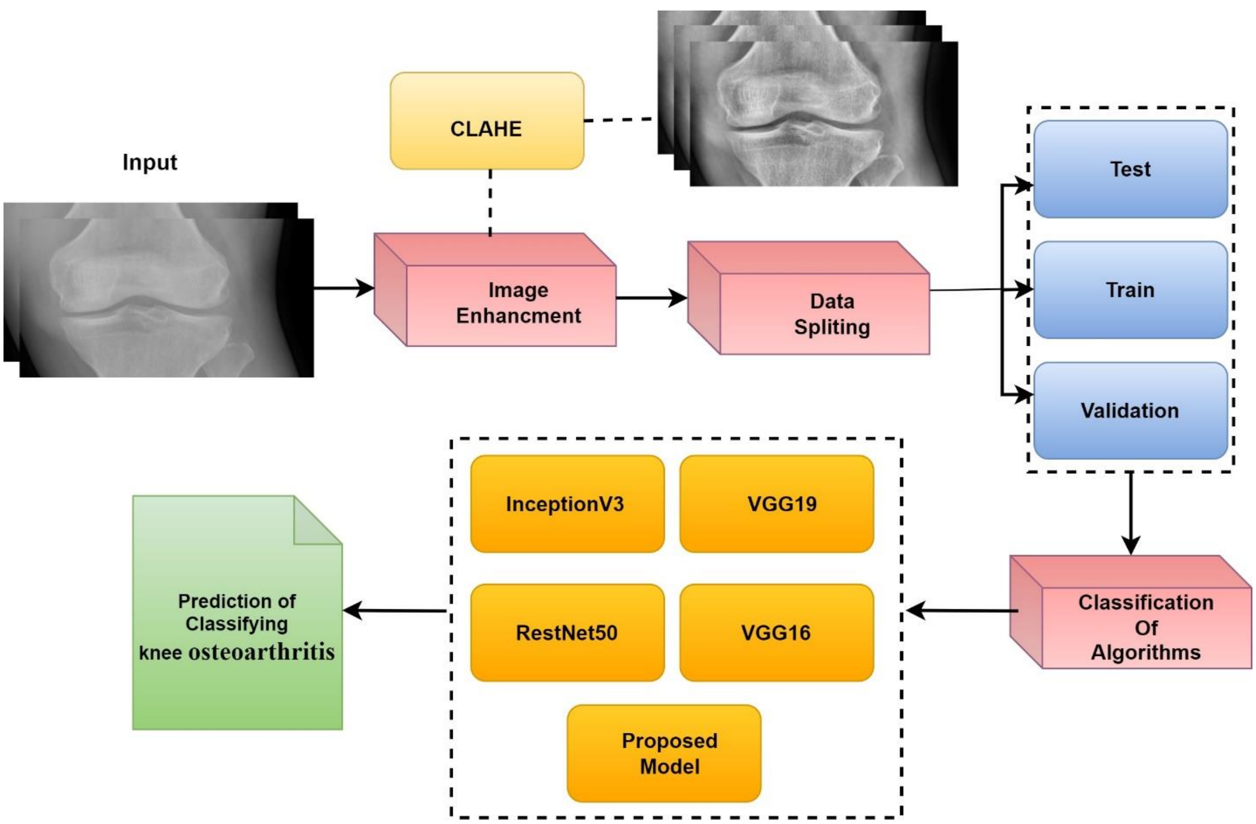

Figure 1: Total Workflow

3.2 Data Description

We obtained the KOA Severity Grading and Digital Knee X-ray Images from Mendeley II [17], and the CGMH KOA Images from Kaggle [18]. These two publicly available datasets provided the data that we used. Each dataset consists of five different grades: grade 0 for normal, grade 1 for dubtful, grade 2 for mild, grade 3 for moderate, and grade 4 for severe. The Digital Knee X-ray Picture Collection consists of 1650 well-curated digital X-ray pictures of the knee joint from recognized medical facilities and diagnostic labs. Two medical professionals have carefully categorized each radiographic knee X-ray image with KL ratings. Additionally, we have developed a novel method based on pixel density to automatically isolate the cartilage area, also known as the region of interest (ROI). We obtained 2050 raw photos after combining the two datasets. Figure 2 displays two different kinds of publicly available datasets. An X-ray machine took the photos, and the originals are in 8-bit grayscale. Table 1 presents all class details of the datasets.

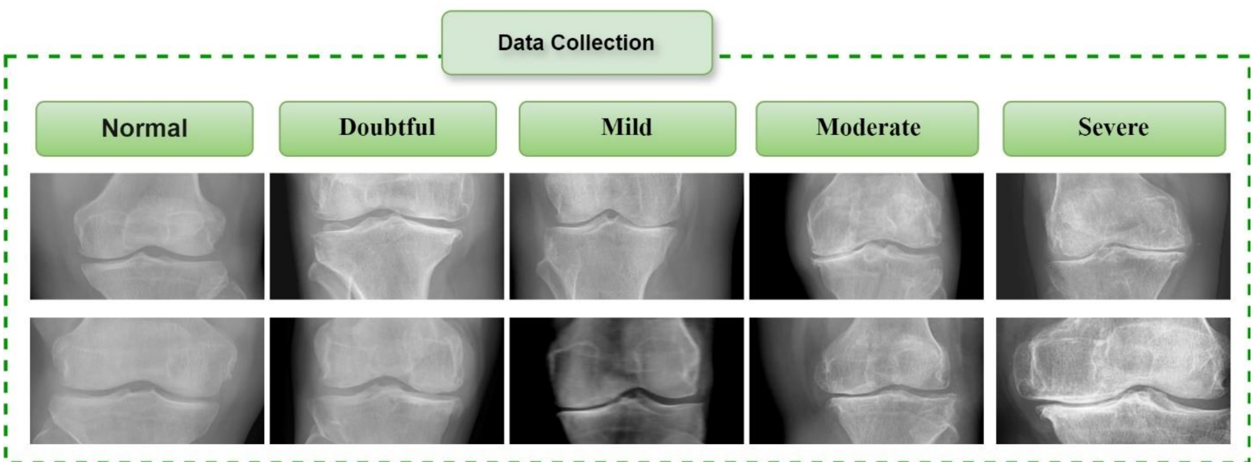

Figure 2: Two type of public dataset

Table-1: Details of Collected Two Dataset

Class	Mendeley II	Kaggle
Normal	503	80
Doubtful	488	80
Mild	232	80
Moderate	221	80
Severe	206	80

However, some of the X-ray pictures in this collection were also of low quality and had damage, so we did not include them all. For this reason, we took 8 sample photos out of the 2050 total. We still used 2042 photos in the study.

3.3 Data Preprocessing

In computer vision tasks, pre-processing is an essential step towards preparing images for analysis and training models. It entails a number of methods to improve picture quality, standardize them, and prepare them for the relevant feature extraction process. It also plays a crucial role in the medical image dataset. It helps to improve the model's accuracy and classify diseases more correctly. However, in this study, we applied CLAHE to improve our dataset.

3.3.1 CLAHE

Using the CLAHE image processing technique, one may increase a picture's contrast and make some features easier to see. The image processing approach efficiently highlights both low and high-frequency components by employing CLAHE, which accounts for the local contrast of various locations in the image [19]. By segmenting the image into smaller tiles and applying histogram equalization to each tile separately, CLAHE prevents noise over-amplification while maintaining overall image quality. Research has also demonstrated the effectiveness of CLAHE in enhancing underwater and medical images, where picture contrast is essential for precise diagnosis and interpretation. In summary, CLAHE is a powerful image enhancement technique that improves contrast and visibility, especially in underwater and medical images. Furthermore, the effectiveness of CLAHE in enhancing multispectral satellite imagery has been studied. The results showed that CLAHE was effective in enhancing the details and edge information in different regions of the electromagnetic spectrum. Also, the effectiveness of CLAHE in enhancing multispectral satellite imagery has been studied. CLAHE is particularly effective for enhancing the local details and edge information of each region in an image. It is an effective technique for improving the visibility of features in images with extreme contrast values [20]. Figure 3 presents the output of our dataset after applying CLAHE. It removes the noise from the image and makes it clearer.

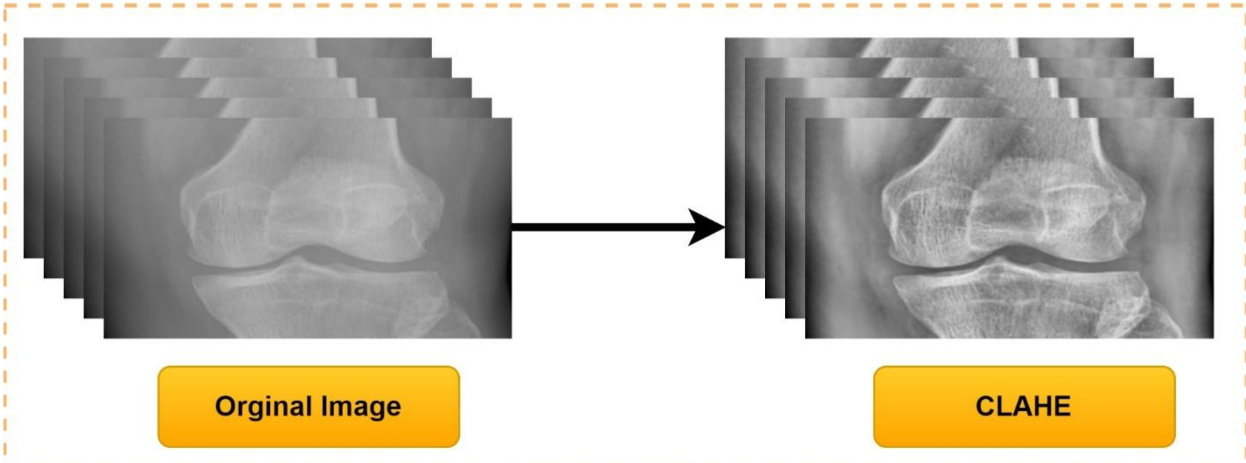

Figure 3: Output Images After Applying CLAHE

3.4 Dataset Splitting

We used a total of 2,042 images in the five classes, with a ratio of 7:1:2. We employed a total of 1,427 training photos, 209 testing images, and 406 validation images in this study. In this manner, we distributed the processed dataset together with the models.

3.5 Algorithm Details

Computers can learn from data and make predictions without explicit programming because of a set of instructions known as deep learning algorithms. There are several varieties of deep learning algorithms, and each has advantages and disadvantages of its own. However, in this research we have implemented InceptionV3, VGG16, ResNet50, VGG19 and a proposed model. This section of the article includes a list of all the models.

3.5.1 InceptionV3

A well-known deep learning model for image classification tasks is InceptionV3, which is known for its effectiveness and precision. By improving upon the success of its predecessors, it reduces computational complexity and boosts performance by improving upon its predecessors' success [21]. The InceptionV3 architecture, a convolutional neural network (CNN), performs object detection and image classification. The first convolutional block, the classifier, and the upgraded inception module are the three separate components of this model, which performs better in object detection. This model heavily uses a 1×1 convolutional kernel to reduce the number of feature channels and speed up training. This model utilizes several layers, including dropout, conventional, max-pooling, average, and fully connected layers, in its construction. Finally, the SoftMax activation function is applied to a fully connected (FC) layer to display the outcome [22].

3.5.2 VGG16

A deep convolutional neural network architecture called VGG16 is well-known for being straightforward and efficient in image categorization applications. VGG16, created by the University of Oxford's Visual Geometry Group (VGG), marked a major turning point in computer vision research with its outstanding performance in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The consistent construction and simplicity of VGG16's architecture distinguishes it. There are three fully linked layers and 13 convolutional layers, totaling 16 layers in this structure [23]. The convolutional layers employ tiny 3x3 filters with a stride of 1 and are followed by Rectified Linear Unit (ReLU) activation functions. The pooling layers use 2x2 max-pooling [24].

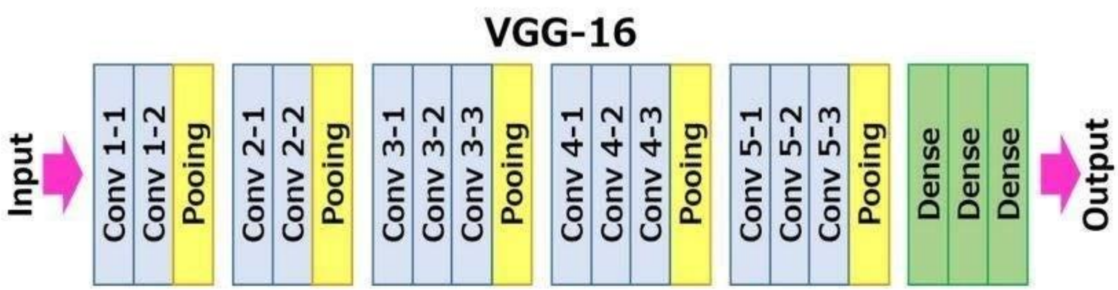

Figure 4: Architecture of VGG16 model

3.5.3 VGG19

VGG19 is the architecture of a deep convolutional neural network. In order to enhance feature extraction capabilities, the architecture adds more layers, but it also maintains the VGG family and particularly follows the design principles of VGG16, its predecessor. VGG19 has a total of 19 weight layers, consisting of 16 convolutional layers and 3 fully linked layers. A softmax output layer is used for classification. Consequently, compared to its equal, VGG16, VGG19 includes three more convolutional layers [25]. For image recognition applications, Daffodil International University 14 has found great success using the very effective model VGG19. The network is a helpful tool for a range of computer vision applications because of its depth, which enables it to understand complex elements at several layers.

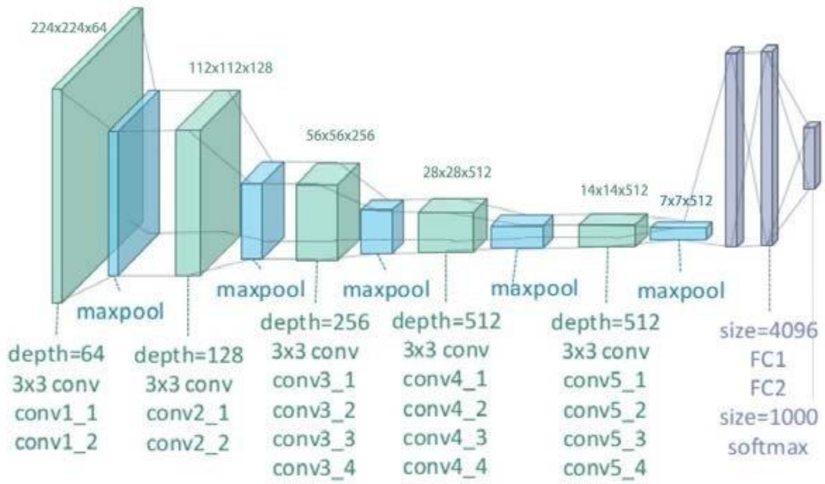

Figure 5: Architecture Details of VGG19 model

3.5.3 ResNet50

To overcome the difficulty of training extremely deep networks, researchers created a very significant deep convolutional neural network architecture called ResNet50. ResNet50's main novelty is the introduction of residual blocks, which enable the network to learn residual functions with reference to the layer inputs. Each residual block learns the residual the difference between the input and the intended output rather than attempting to learn the underlying mapping directly. ResNet50, as its name suggests, comprising batch normalization, ReLU activations, convolutional, pooling, and fully connected layers. There are fifty levels in this architecture's model. There is a shortcut path in this model to get to the end state, and it helps to avoid the odd layers during training, which speeds up the process overall. There are about 23 million parameters in this model [26].

$$y = F(x) + x$$

- F(x) = The transformation or mapping
- x, y = Showing activations or function mappings

The addition operation F(x)+x refers to the connection that goes around one or more convolutional layers. It helps the network find residue mappings, which makes deep learning optimization easier.

3.6 Proposed Methodology

The Our suggested model is a deep learning method that combines LSTM models with soft attention. The model comprises several layers, each handling the incoming data differently [27]. The model uses the input form (224, 224, 3) to represent pictures with a resolution of 224x224 pixels and three color channels. The initial layers consist of max-pooling and convolutional processes that progressively lower the data's dimension. Following each of these layers is a soft-attention layer, which employs attention mechanisms to highlight important features using max-pooling strategies. In order to compress and prepare the data for processing, this layer splits its outputs into two halves, which it then combines to create a composite representation of the activation dropout characteristics of the subsequent layers [28]. We use a reshape layer to convert the data into a 16x8 matrix. The LSTM layer receives this matrix and uses frequent connections to identify sequential patterns. A thick layer with four output units completes the categorization process. Figure 6 displays the architecture of our suggested models.

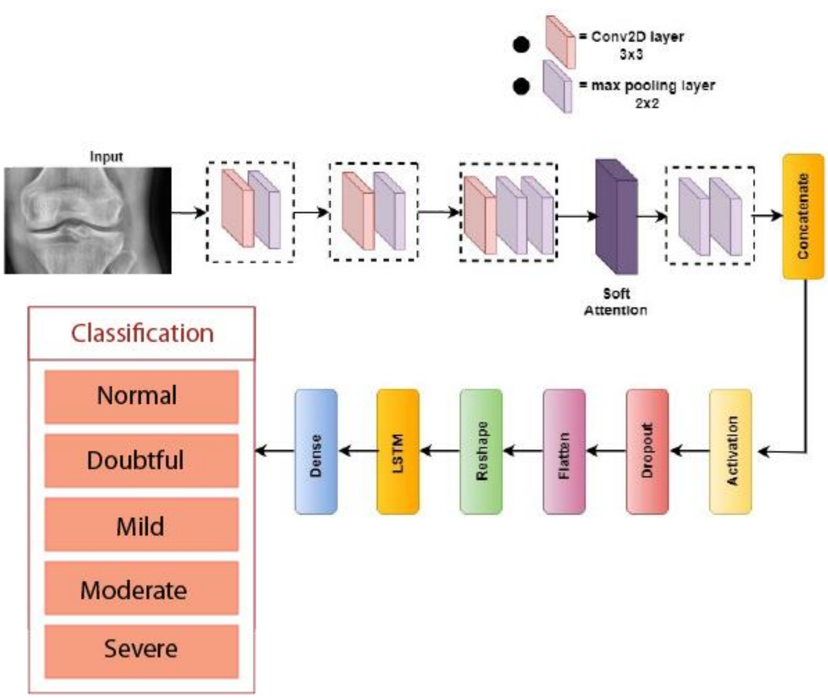

Figure 6: Architecture of our proposed model

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experiment Result

Table 2 compares test accuracy for different deep learning architectures after 160 training epochs. We have assessed InceptionV3, VGG16, VGG19, ResNet50, and a proposed method among the architectures. InceptionV3 is well-known for its efficient use of factorized convolutions and auxiliary classifiers to improve learning. It is good that the model's test accuracy is 90%. The VGG16 has a respectable test accuracy of 88.87%, but it performs slightly worse than InceptionV3, despite its simplicity. In the VGG19 model, the test accuracy drops to 85.60%. This could be due to overfitting or an increase in model complexity without a corresponding improvement in performance. ResNet50's use of residual learning with identity shortcut connections facilitates deeper network training. In this case, the model's test accuracy of 61.09% is much lower than expected. The proposed approach achieves an amazing 96.56% test accuracy, outperforming all other evaluated architectures.

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Architectures	Epoch	Test Accuracy (%)
InceptionV3	160	90
VGG16	160	88.87
VGG19	160	85.60
ResNet50	160	59.79
Proposed Method	160	96.56

Table 2: Accuracy Table

4.2 Loss and Accuracy Curve of all Models

Figure 7-11 displays the accuracy and losses in training and validation for each of the models. The vertical axis of the graph displays the model's losses, while the horizontal axis represents the number of learning cycles, or epochs. The graph displays the distinction between validation and training sets as each model learns again. The validation graph first declines and then steadily rises when the model is a good fit for the training set.

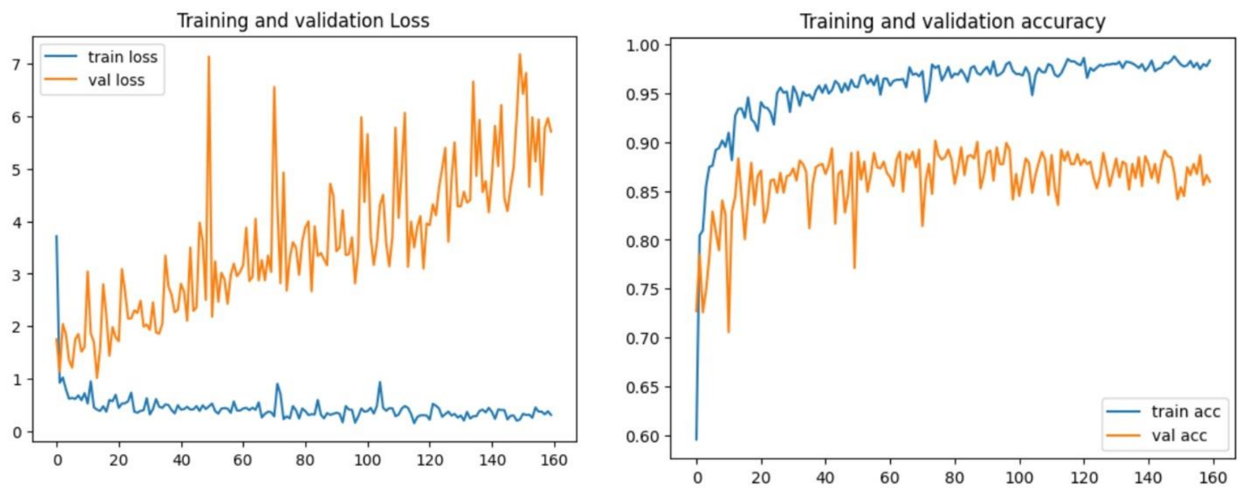

Figure 7: Accuracy and Loss Curve of Inception V3

Image recognition research frequently uses the InceptionV3 model. Researchers built this convolutional neural network using a learning model. It has significantly increased in comparison to V1. Compared to its previous version, it is more accurate. The model's accuracy and loss curves during the training and validation stages frequently illustrate the Inception V3 model's intricate architecture and ability to recognize difficult features. Low accuracy is the result of the model's large losses during training and validation in the first few learning epochs. Effective learning is demonstrated by training accuracy increasing and training loss typically declining gradually over time. However, there is frequently more variation in the validation loss and accuracy. Good generalization to unobserved data should ideally be shown by a decrease in validation loss and an improvement in validation accuracy. Figure 7 displays the accuracy and loss curve of the InceptionV3 model for KOA.

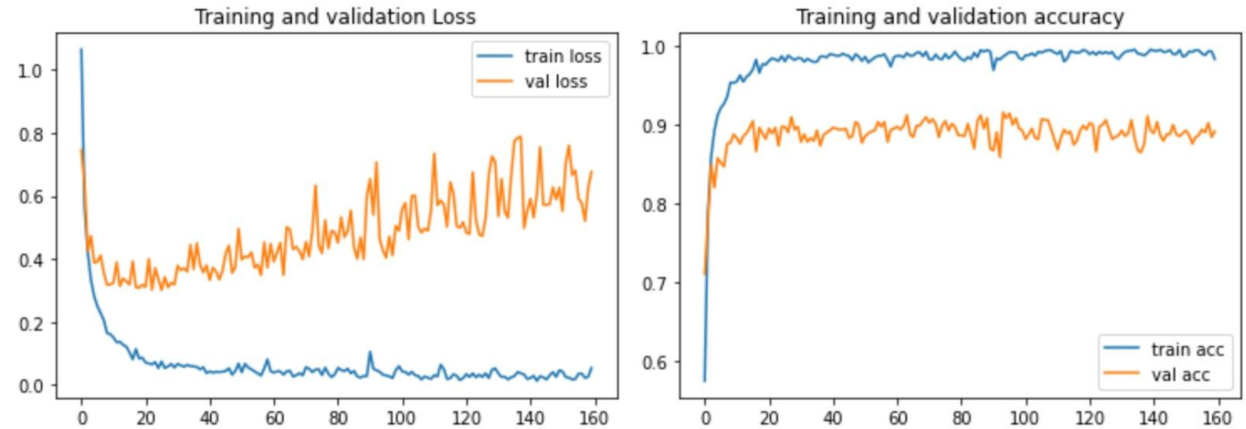

Figure 8: Accuracy and Loss Curve of VGG16

VGG-16 can also be used for object identification and classification. You can categorize a thousand photos into a thousand distinct categories. This approach is the most widely used because it is simple to apply to transfer learning. Figure 8 displays the accuracy and loss curve of the VGG16 model. The provided figure 9, display the accuracy and loss during training and validation for Resnet50 model over several epochs. In the left plot, the training loss is represented by the blue curve and the validation loss by the orange curve. While learning progress is shown by the general decrease in both losses over time, the validation loss is considerably more unpredictable, displaying big spikes that might be indicative of noise or overfitting in the validation data.

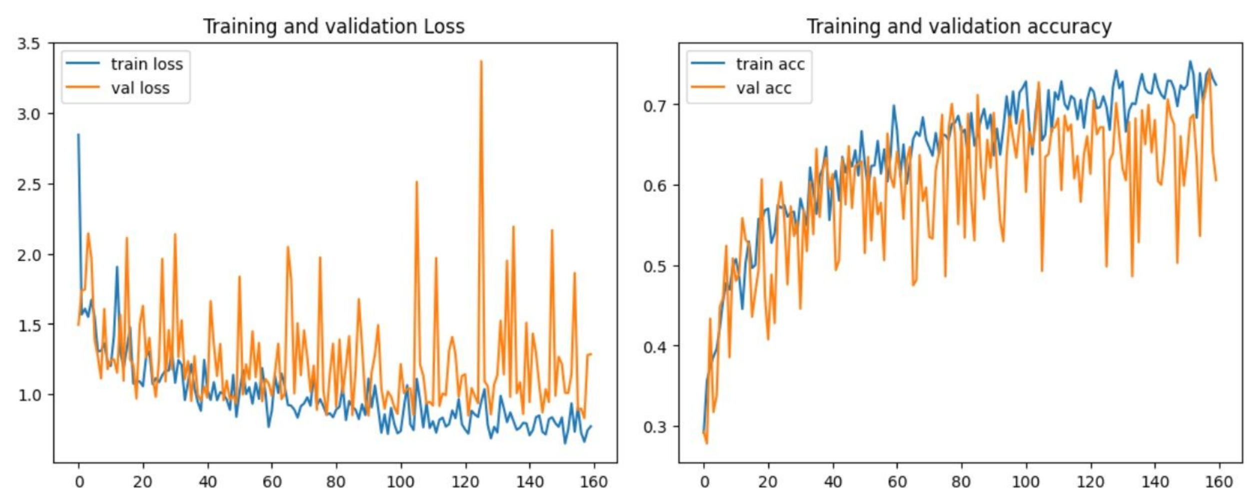

Figure 9: Accuracy and Loss Curve of ResNet50

Two curves in the illustration on the right side indicate the accuracy. The orange curve represents the validation accuracy, while the blue curve represents the training accuracy. As the training accuracy continuously surpasses the validation accuracy, the accuracies steadily increase over time. This is a regular occurrence, and if the discrepancy is large, it may indicate overfitting. If there are discernible differences in the validation accuracy, it is possible that the model is not operating consistently on the validation set. Regularization strategies like dropout, L2 regularization, or data augmentation can reduce overfitting. Furthermore, by applying cross-validation techniques and stopping early based on validation loss.

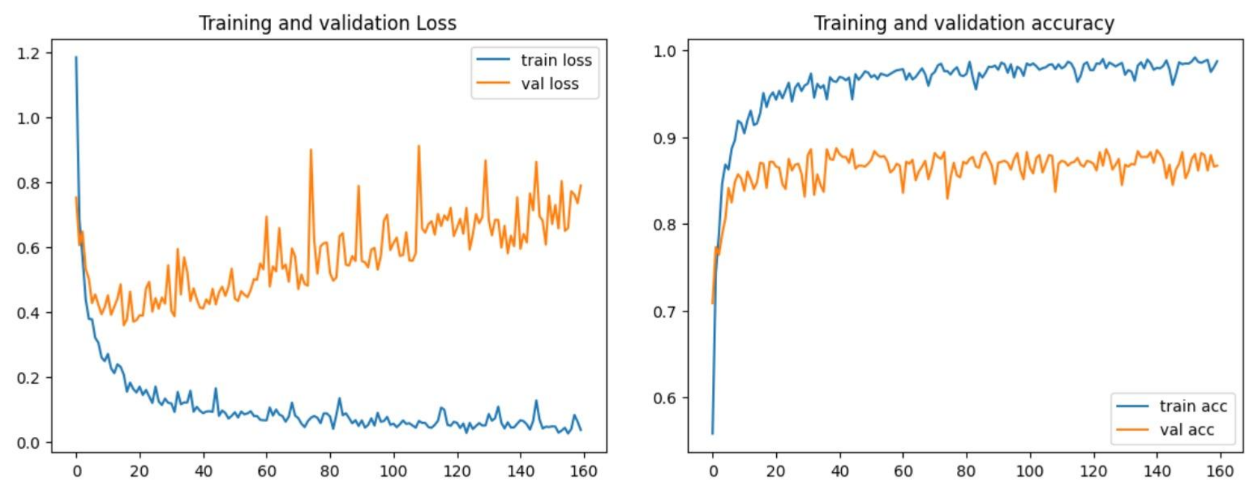

Figure 10: Accuracy and Loss Curve of VGG19

Accuracy and loss curves for the VGG19 model often exhibit unique patterns throughout training and validation, indicating the possibility of overfitting and the model's learning experience. Figure 10 presents the loss and accuracy curve of VGG19 model. Since the accuracy is low and the early epoch training and validation losses are significant, the model is still in its early learning phase. The training loss gradually decreases and the accuracy rises as training progresses, demonstrating the model's increasing performance on the training data. On the other hand, the validation curves may display a more erratic pattern.

In an ideal world, validation loss would drop and accuracy would rise, reflecting training patterns but often with more unpredictability. If the training accuracy much exceeds the validation accuracy and the validation loss begins to climb while the training loss continues to decline, the model is likely overfitting, which occurs when the model performs well on training data but poorly on unknown data. Early stopping and regularization techniques like dropout or weight decay, which prevent the model from becoming unduly specialized in the training set, can help to alleviate this. Figure 11 shows the loss and accuracy curves of our proposed model. It shows that our proposed model outperforms different deep learning models.

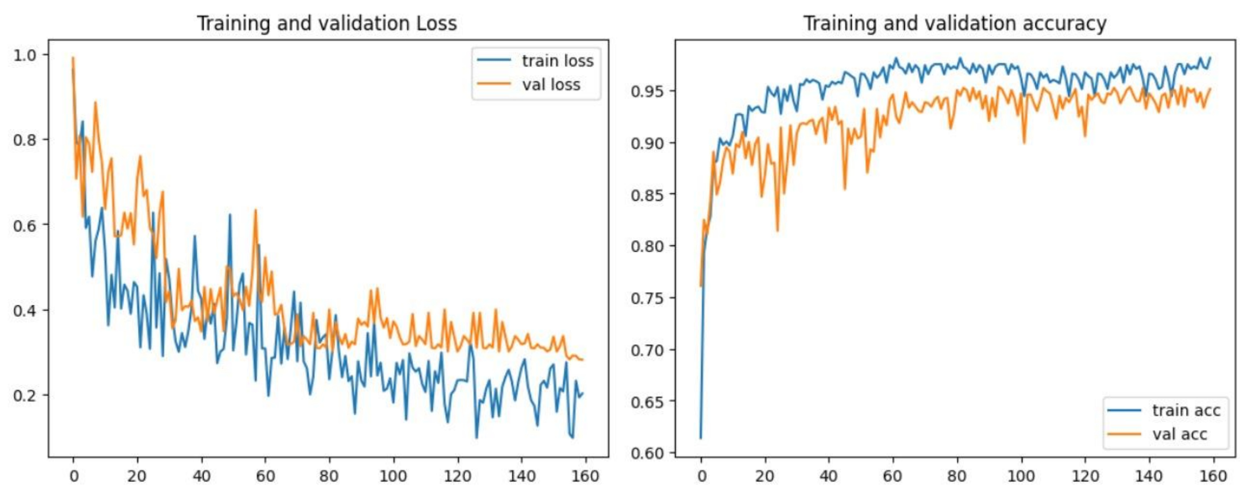

Figure 11: Accuracy and Loss Curve of Proposed Model

4.3 Comparison Analysis

COMPARISON BETWEEN EXISTING LITERATURE AND OUR PROPOSED MODEL BASED ON ACCURACY

Problem Domain	**Apply image pre-processing techniques**	**Classifier**	**Accuracy**	**References**
classification	N/A	DST-DNet, DST-CNN	68.70%	[10]
detection	N/A	Classic CNN for X-ray images, and 3D CNN for MRI images.	50% for CNN, 54% for MRI	[11]
classification	Yes	CNN	87%	[12]
classification	N/A	ResNeXt-50	86.9%	[14]
classification	Yes	ResNet-18	84.09%	[15]
classification	Yes	**Proposed model**	**96.56%**	**This Work**

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The creation and use of a strong deep learning method for the diagnosis and categorization of knee osteoarthritis (KOA) can have significant effects on society, especially in the areas of patient outcomes, healthcare, and cost effectiveness.

Improved Diagnostic Accuracy: Conventional techniques for identifying osteoarthritis in the knee frequently depend on radiographic examinations and clinical evaluations, both of which are labor-intensive and prone to human error. Diagnoses may be made more quickly and with more accuracy when a deep learning technique is used to examine medical pictures. As a result, radiologists and orthopedic experts are less burdened and may concentrate on treating more complicated situations and procedures.

Enhanced Early Detection: Effective management and treatment of osteoarthritis in the knee need early identification. Deep learning algorithms can be used to detect early indications of knee osteoarthritis (KOA), possibly even prior to the onset of noticeable symptoms. Early management can save long-term healthcare expenses related to advanced KOA, enhance patient quality of life, and halt the disease's development.

Reduced Healthcare Costs: The healthcare system may save a lot of money if osteoarthritis in the knee is accurately and promptly diagnosed. Early management can avoid the need for more costly procedures like joint replacements. Furthermore, accurate and effective diagnostic technologies cut down on the number of consultations and diagnostic tests required, which streamlines patient care and lowers total healthcare costs.

Empowering Remote and Underserved Communities: Deep learning techniques for OA categorization can also help underprivileged and isolated areas with limited access to specialists in medicine. Patients in remote or low-resource locations can get accurate diagnosis and recommended courses of therapy without having to travel far by incorporating these models into telemedicine systems.

Advancing Medical Research: Deep learning models can yield data and insights that have the potential to greatly advance medical research. Large dataset analysis allows researchers to find previously unidentified patterns and connections in knee osteoarthritis, which advances our knowledge of the condition and inspires the creation of fresh approaches to therapy. Patients' long-term prognosis may be enhanced by this never-ending learning loop and advancements in the care of osteoarthritis.

Ethical and Societal Considerations: Despite the significant advantages, ethical and societal issues surrounding the application of deep learning to medical diagnostics must be addressed. It is critical to protect patient data's confidentiality and privacy. Furthermore, the decision-making process used by these models has to be transparent, and any biases that can result in care inequalities need to be removed.

Overall, a robust deep learning strategy for classifying knee osteoarthritis has the potential to completely change how KOA is diagnosed and treated, resulting in better patient outcomes, more individualized treatment, financial savings, and advances in medical research. This technology has the potential to significantly improve healthcare delivery and quality of life for millions of individuals with knee osteoarthritis by tackling ethical and societal issues.

5.2 Impact on Environment

The use of a strong deep learning strategy for the categorization of knee osteoarthritis (KOA) can also benefit the environment in a number of ways, mostly by increasing productivity and reducing the amount of resources used:

- ➢ **Reduction in Physical Resource Use:** When using radiographic films, multiple imaging sessions, and physical medical record storage, traditional diagnostic methods can have a significant negative impact on the environment. However, a deep learning approach that makes use of digital imaging and cloud-based storage can significantly reduce the need for physical materials.
- ➢ **Minimization of Medical Waste:** Repeated and duplicate testing are not as necessary when diagnoses are made earlier and with greater accuracy. As a result, less medical waste—such as old radiography films, throwaway equipment, and other items that are usually thrown away after a single use—may be produced. Lowering medical waste also eases the strain on waste management systems and the environment.

- ➢ **Resource-Efficient Healthcare Delivery:** The use of deep learning in knee OA categorization can result in a healthcare delivery system that is more resource-efficient. Healthcare providers may reduce their total environmental impact by allocating resources more effectively through the optimization of diagnostic processes and the reduction of needless operations. Reduced utilization of auxiliary supplies and utilities is another benefit of optimizing the use of medical resources.
- ➢ **Support for Sustainable Practices in Healthcare:** The adoption of more comprehensive sustainable practices in the healthcare industry may be aided by the use of deep learning into diagnostics. To further promote environmental sustainability, healthcare facilities can be encouraged to invest in digital infrastructure and energy-efficient data centers. The global push to promote green technology and lower carbon emissions is in line with the trend toward digital transformation in the healthcare industry.

In conclusion, by minimizing medical waste, lowering the carbon footprint from patient travel, promoting resource-efficient healthcare delivery, and reducing the use of physical resources, a strong deep learning approach for knee osteoarthritis disease classification can have a positive effect on the environment. Furthermore, more comprehensive environmental and public health activities may be supported by the insights obtained by data analysis.

5.3 Ethical Aspects

There are several ethical issues with the creation of a strong deep learning method for knee osteoarthritis (KOA) disease categorization. First and foremost, it is critical to protect patient privacy and data security as using sensitive medical data calls for strict security measures to prevent breaches and abuse. It is also necessary to consider the possibility of algorithmic bias in order to avoid discrepancies in diagnosis accuracy between various demographic groups. It is crucial that the decision-making process of these models be transparent, necessitating open communication on the standards and procedures followed by the algorithms. Accountability procedures must to be in place to handle any mistakes or incorrect diagnoses brought on by technology. Furthermore, it is important to consider how easily accessible this sophisticated diagnostic instrument is. This will guarantee that all patients, irrespective of their financial situation or geographic location, may take advantage of the enhanced precision and effectiveness it provides. Innovation must be deployed ethically while maintaining justice, equity, and respect for the rights and autonomy of patients.

5.4 Sustainability Plan

A strong deep learning strategy for knee osteoarthritis (KOA) condition categorization should be implemented with a sustainability plan that includes many essential components. First and foremost, the system needs to be built with long-term scalability in mind, enabling constant modifications and enhancements to the algorithms in light of fresh data and technological breakthroughs. To maintain high accuracy and relevance, a framework for routine model retraining and validation must be established. To reduce the environmental impact, cloud-based infrastructure and energy-efficient computer resources should be used. A thorough data governance framework that prioritizes privacy and security must also be in place to guarantee the moral gathering, storing, and use of patient data. Ongoing training programs for medical personnel will assure successful usage and trust in the technology, while collaborative relationships with researchers, legislators, and healthcare providers can encourage wider acceptance and incorporation into clinical processes. The system's economic feasibility should also be considered to ensure that it is implemented and maintained in a way that will benefit patients and the healthcare system in the long run at a reasonable cost.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusions

Osteoarthritis (OA) is a common degenerative joint condition that causes pain, stiffness, and limited mobility due to the progressive loss of cartilage in the knee joint. Aging, being overweight, having had prior knee injuries, recurrent stress on the joint, and genetic susceptibility are common risk factors. In this research on knee osteoarthritis (KOA) using Image Processing, five deep learning algorithms, namely VGG16, ResNet50, VGG19, InceptionV3 and a proposed model, were assessed on how well they identified KOA disease. The experimental findings provided insight into how well each algorithm performed in terms of accuracy and loss. Our carefully selected dataset consists of two different sets of X-ray images with different resolutions and quality levels. We used image processing techniques to enhance the quality of all 2042 images in our dataset because the noise and artifacts in these images caused issues. Our suggested model astonishingly performed exceptionally well, with an accuracy percentage of 96.56%.

Compared to conventional deep learning models, the suggested model that we presented performed better, particularly when it came to the multiclass categorization of multiple low-pixel X-ray images. In future, another potential topic to investigate is the segmentation of ROIs from pictures using 3D reconstruction and graphical domains such as geometric deep learning (GDL) and graph neural networks (GNN). This improvement can lead to an even more dependable and strong categorization performance. Despite a few drawbacks, the model is notable for its resilience and dependability, indicating its potential as a useful tool in the field of medical imaging.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: A Robust Deep Learning Approach for Knee Osteoarthritis Disease Classification

Student ID: 201-15-13644

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate knowledge from recent and previous studies to identify the issue of knee osteoarthritis classification for the Final Year Design Project (FYDP).	**PO1**
CO2	Analyze and establish various design goals for creating an intelligent model using image processing and deep learning techniques.	**PO2**
CO3	Conduct a comprehensive literature review, identify key challenges, and set objectives for developing the intelligent model for knee osteoarthritis classification.	**PO4**
CO4	Perform economic evaluation, cost estimation, and apply suitable project management techniques throughout the development of the FYDP.	**PO11**
Phase -II		
CO5	Develop technical solutions and components for the model, ensuring compliance with public safety standards and consideration of social and environmental impacts.	**PO3**
CO6	Utilize appropriate methodologies, resources, and modern engineering and IT technologies to address complex engineering problems in predicting and classifying knee osteoarthritis.	**PO5**
CO7	Evaluate societal, health, safety, and cultural implications in professional practice and problem-solving for the FYDP.	**PO6**
CO8	Assess the sustainability and long-term impact of the developed model within social and environmental contexts.	**PO7**
CO9	Implement ethical principles and adhere to professional standards throughout the project.	**PO8**

CO10	Demonstrate the ability to work effectively both independently and as a team leader or member in diverse and multidisciplinary environments.	**PO9**
CO11	Communicate effectively with the engineering community and the broader society regarding complex engineering activities, including writing reports and providing clear instructions.	**PO10**
CO12	Recognize the importance of continuous learning and possess the ability to engage in self-directed and life-long learning amidst evolving technological landscapes.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO4, CO5, CO6, CO7, CO8	This project demonstrates fundamental engineering (K3) principles by employing deep learning models like ResNet50, VGG19, InceptionV3, VGG16, and the proposed model for analyzing and classifying knee osteoarthritis in X-ray images. Specialist knowledge (K4) is applied through the exploration of different deep learning architectures, enhancing the detection of osteoarthritis in medical images. It also applies engineering practice & technology (K6) by implementing and evaluating different deep learning models for the classification task. The project synthesizes insights from recent studies (K8) to advance the detection of osteoarthritis using image processing and deep learning techniques.	**Page no:** [6-9,11-13,18-21] **Section:** [2.1, 2.2, 2.3, 2.4, 3.2, 3.4, 4.2]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses EP-2 by recognizing the challenges in detecting knee osteoarthritis, including limitations of traditional image processing methods and the complexities of integrating various deep learning approaches. It confronts issues in understanding visual nuances and offers insights for refining detection methodologies.	**Page no:** [10-16] **Section:** [2.2, 2.3, 4.2]
3.	**EP3: Depth of analysis required**	Yes	CO2, CO6	This project addresses EP-3 by meticulously comparing experimental outcomes, highlighting the performance of various models like ResNet50, VGG19, and the proposed model as significant solutions for enhancing the detection of knee osteoarthritis.	**Page no:** [8,18-21] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science, impacting medical diagnostics by analyzing X-ray image for knee osteoarthritis, contributing to advancements in medical practices and interventions.	**Page no:** [1,6-9] **Section:** [1.1, 2.1, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components such as data collection, image processing techniques, and proposed methodology, ensuring a holistic solution to complex challenges in detecting knee osteoarthritis.	**Page no:** [11-13] **Section:** [3.2, 3.3, 3.4]
8.	**EP8: Consequences for society and the environment**	Yes	CO8	The project examines the societal implications of detecting osteoarthritis in medical images, addressing ethical concerns and the impact of timely intervention in healthcare, promoting responsible and beneficial use of AI for societal well-being.	**Page no:** [23-24] **Section:** [5.1, 5.3]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our thesis utilizes diverse resources such as high-performance computing infrastructure, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in detecting osteoarthritis through image processing and deep learning.	**Page no:** [13-15] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	Yes		The project applies innovative image processing techniques and deep learning models for detecting osteoarthritis in X-ray images, showcasing the use of state-of-the-art methods in addressing medical issues.	**Page no:** [10-16, 18-22] **Section**: [3.2, 3.4, 4.2]

4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare support through advanced detection methods for osteoarthritis, while also addressing ethical concerns and promoting responsible data usage.	**Page no:** [23-26] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		The project expands upon existing research by exploring advanced image processing and deep learning methods for analyzing X-ray images, providing new insights into detecting knee osteoarthritis.	**Page no:** [6-9] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses CO4 by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [5] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing data privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of AI for healthcare.	**Page no:** [11] **Section:** [5.3]
3	CO10	Yes	The project includes effective communication strategies for presenting findings and engaging with the academic community, as well as developing comprehensive documentation and clear instructions for the implemented models.	**Page no:** [1-5, 18-21] **Section:** [1.1, 4.2]
4	CO12	Yes	The project's dedication to continuous learning and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [11-16, 17-22] **Section:** [3.2, 3.3, 3.4, 4.2]

Plagiarism Report:

A ROBUST DEEP LEARNING APPROACH FOR KNEE OSTEOARTHRITIS DISEASE CLASSIFICATION

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