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DETECTION OF KNEE OSTEOARTHRITIS USING CONVOLUTIONAL NEURAL NETWORKS (CNN)

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Abstract:A frequent kind of arthritis, knee osteoarthritis is characterized by sclerosis, joint space narrowing, osteophyte growth, and bone deformities that can be seen on radiographs. Radiography is the most affordable and widely accessible method, and it is considered to be the best. The Kellgren and Lawrence (KL) grading technique is used to classify X-ray pictures in accordance with the progression of osteoarthritis from normal to severe. Degeneration of osteoarthritis in the knee can be slowed down by early identification, which can aid in early treatment. Regretfully, in an effort to enhance the performance of their models, the majority of currently used methods either combine or eliminate confusing grades. The objective of this research is to present an approach by leveraging an ensemble of CNN models, specifically MobileNet, ResNet, and AlexNet architectures. The choice of using a Convolutional Neural Network (CNN) for knee osteoarthritis classification is driven by its capacity to leverage deep learning techniques for medical image analysis. CNNs excel at feature extraction from medical images, making them ideal for identifying subtle patterns indicative of osteoarthritis. This approach improves the potential to automate diagnosis, reduce human error, and patient outcomes by enabling timely intervention, underscoring its relevance in the realm of medical image analysis. An Osteoarthritis Initiative (OAI) based dataset of knee joint X-ray images is chosen for this study. The dataset was split into the training, testing, and validation set with a 7.5: 1.5: 1 ratio. Our results shows that the ensemble approach significantly outperforms individual model predictions, achieving an accuracy of 96%. This improvement underscores the potential of using deep learning ensembles in medical image analysis, offering enhanced diagnostic processes in KOA classification.

Keywords: Knee Osteoarthritis (KOA), Osteoarthritis dataset, CNN, AlexNet, ResNet, Mobile Net, Ensemble model

I.INTRODUCTION

Multiple factors contribute to the difficulty of diagnosing, detecting, and treating osteoarthritis (OA) [1]. It is a long-term degenerative condition that causes cartilage to deteriorate and finally breaks down bones. One kind of osteoarthritis that affects the knee joint is called knee osteoarthritis (KOA). Pain, stiffness, swelling, and restricted joint movement are examples of physical symptoms. Age, gender, race, genetics, obesity, injuries, low vitamin D levels, and lifestyle choices are risk factors [1]. There are many phases of severity and the disease progresses over time. A recent study [2] found that 16% of people worldwide had KOA. The World Health Organisation (WHO) reports that this condition affects adults over 60 globally and is more common in women (18.0%) than in males (9.6%) [1]. X-rays, arthroscopy, magnetic resonance imaging [MRI], and symptoms are typically used to diagnose knee osteoarthritis. But OA's early phases are frequently concealed. Furthermore, there is only a limited correlation between the image-represented severity level of OA and the degree of pain and impairment. Therefore, a more accurate diagnostic method

is required to identify OA in its early phases. In this case, OA-related biomarkers may be useful [1].

The basis for identifying and treating KOA is the use of radiographs or X-rays to evaluate restlessness and pain [1].Cyst formation, subchondral sclerosis, osteophytes, and joint space narrowing (JSN) are important characteristics that can be seen on X-rays. The lack of protective cartilage between knee joints is referred to as JSN. A bony bump developed on bones or joints is called an osteophyte, and abnormal increase in bone density is called subchondral sclerosis.

A semiquantitative technique for assessing radiographs (x-rays) for KOA severity is the Kellgren and Lawrence's (KL) grading system [5]. This approach assigns ordinal numbers based on the degree of severity for classification. Table 1 describes the KL grades. A lot of automated techniques and medical grading systems misclassify a KL grade to its adjacent grade, making them less trustworthy. Furthermore, given the scarcity of morphological and feature modifications in subsequent KL grades, it gets harder to distinguish between different grades[6]. The mainstream studies treat it as a multi-class classification task and ignore the inherent ordinal nature within KL grades [6].

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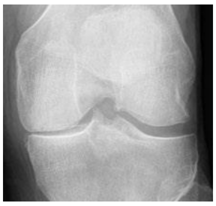
While the most challenging stages of KOA are combined for classification in certain research, the majority of studies find limited accuracy in the earliest stages [7], [3], and [8]. Simultaneously, certain approaches attempt to enhance performance by merging X-ray features with additional clinical data [10]. Consequently, knee deterioration that requires a total knee replacement can be prevented if it is detected and treated early enough. In order to stop the disease from developing and getting worse, we need a helping tool.

We have made an effort to close this gap in this study by raising the prediction accuracies for every KL grade. A ten-year prospective observational study of KOA involving multiple centres is called the Osteoarthritis Initiative (OAI). With funding from the National Institutes of Health (a division of the Department of Health and Human Services), they enrolled 4796 men and women. The data they used came from over 431,000 imaging and clinical visits, and there were about 26,626,000 images in this archive. Our study's knee X-ray pictures were taken from this dataset [4].

TABLE 1. Kellgren and Lawrence's grading (KL) grading scheme

Image	Grade Description
	Grade 0 (Normal) is assigned to normal bones and no symptoms on X-rays.
	Grade 1 (Doubtful) depicts doubtful JSN and the possibility of osteophytes.
	Grade 2 (Mild) specifies definite osteophytes and possible JSN.
	Grade 3 (Moderate) indicates multiple osteophytes with possible bone deformity.
	Grade 4 (Severe) shows large osteophytes, definite JSN, and severe sclerosis.

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1) Our technique does not require images from different perspectives or other clinical data; it may be applied to unilateral posteroanterior knee X-rays.
2) Four pre-trained models based on ImageNet were refined. These models each produce state-of-the-art outcomes on their own.3)To increase overall performance, forecasts from the previously mentioned base models are combined to create an ensemble model. 4) A customised ordinal loss function is used to examine ordinal classification.
5) Lastly, class-specific heatmaps are used to visualise the model's main features.

Our goal was to increase the model's performance across all grades while concentrating on early KOA detection. Physicians can develop a more effective early KOA treatment plan with the aid of early diagnosis and accurate KOA grade prediction, which will also save patient costs associated with delayed discovery.

II. RELATED WORK

Chen et al.'s [7] completely automated knee joint identification system makes use of the YOLO2 Network. They have evaluated a number of optimised networks, including ResNet, VGG, and DenseNet, for classification. Their mean absolute error is 0.344 and has a maximum accuracy of 69.7%.

Thomas et al. [11] created an automated CNN-based model for assessing knee osteoarthritis severity from radiographs. They utilized 32116 training photos, 4074 tuning images, and 4090 testing images. They received an F1 score of 0.70 for the test set, and they reported accuracy of 0.71.

A different study [9] used the OAI dataset to extract 25873 training images, 7779 validation images, and 5941 testing images. Using U-Net, the left and right knee joints are localised. Demographic data is input into DenseNet, including age, gender, and BMI. Their approach produced sensitivity values for four different levels of OA: moderate (68.9%), mild (70.2%), normal (83.7%), severe 86.0%, and Specificity normal 86.1%, mild 83.8% moderate 97.1%, and severe 99.1%. The KL1 dubious grade has been dropped. Additionally, their internal radiologists point out that the KL classification's inter-observer reliability ranges from 0.51 to 0.89. It has also been noted that nearby KL grades are typically the target of these incorrect categorization.

Pretrained ResNet-34 architecture was used in a transfer learning-based manner [10]. They made use of 728 individuals' OAI data. The algorithm is fed knee radiographs and additional clinical data, such as age, gender, ethnicity, and BMI, in order to predict potential KL grade and OA progression. Their obtained AUCs for KL grade prediction using transfer learning are 0.93, 0.80, 0.88, 0.96, and 0.99.

III. METHODOLOGY

We have outlined the entire technique used in this study to accomplish the goals listed above in the section that follows. The dataset is first described in Section III-A. The pre-trained deep learning networks that we employed in our experiments are then described in Section III-B. Finally, The training procedure and experimental parameters are described in Section III-C.

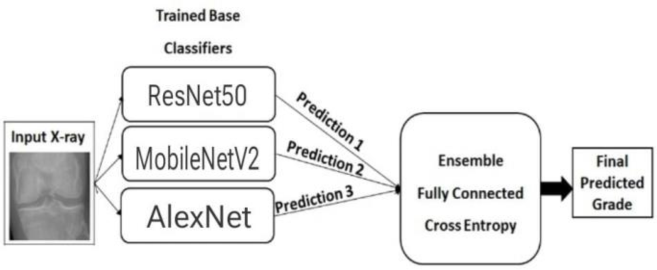

Figure 2: Ensemble Architecture

A. DATASET DESCRIPTION

The Osteoarthritis Initiative dataset served as the basis for the dataset used in the present study [12]. The KL grading scheme has been applied to 9786 X-ray pictures. There are 3857 images in grade 0, 1770 in grade 1, 2578 in grade 2, 1286 in grade 3, and 295 in grade 4 respectively. Every image has a size of 224 × 224.

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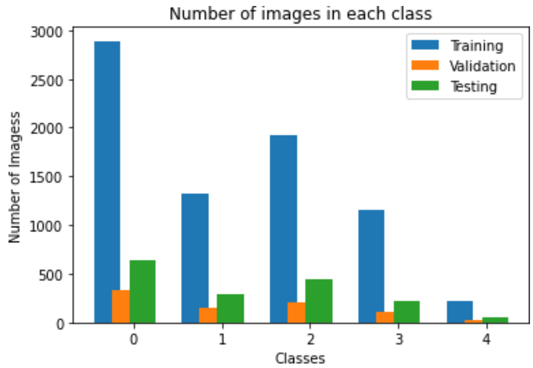

Figure 1: No. of images

Due to the extreme imbalance in the data, it has been divided into train, test, and validation classes based on the quantity of samples that are accessible for each category. The data distribution for training, testing, and validation is shown in Figure 1. The partitioning utilised by [7] and [13] is the same.

B. NETWORKS

This paper outlines the methodology employed in the highlighting the unique contributions of each architecture, training procedures, and validation techniques. Through this we work to contribute to the advancement of deep learning-based orthopaedic diagnostics, ultimately improving patient care and treatment outcomes. Here's a breakdown of its functionality within this project:

Convolutional Layers:

The ensemble model incorporates convolutional layers from each base model (MobileNet, ResNet, and AlexNet). These convolutional layers serve as feature extractors, capturing hierarchical representations of knee X-ray images. Each base model contributes unique filters and convolutional operations, enabling the ensemble to learn diverse features indicative of knee injuries.

ReLU Activation:

Following each convolutional layer, Rectified Linear Unit (ReLU) activation functions are applied independently. ReLU introduces non-linearity into the model, flowing it to learn complex patterns and relationships within the data. This activation function helps in capturing subtle details and enhancing the model's discriminative power.

Pooling Layers:

Max-pooling layers are coordinated into the gathering model after chose convolutional layers. These layers down sample the element maps got from the convolutional layers. diminishing spatial aspects while holding fundamental data. Max-pooling improves computational proficiency and guarantees that the model spotlights on the most striking elements for knee injury discovery.

Fully Connected Layers:

After the convolutional and pooling layers, the outfit model integrates completely associated layers for characterization. These layers aggregate features extracted by the convolutional layers and make predictions regarding knee injury severity. Each base model contributes its set of fully connected layers, allowing the ensemble to integrate diverse feature representations for accurate classification.

Training:

During training, the ensemble model learns to classify knee X-ray images using a combination of features extracted by MobileNet, ResNet, and AlexNet. The model's parameters are optimized through backpropagation and gradient descent. minimizing a predefined loss function. Training involves iteratively adjusting the weights and biases of the model to improve its predictive performance.

Utilizing convolutional layers to extract features and fully connected layers for classification, ensemble proves to be a powerful deep learning architecture for identifying knee injuries from X-ray images. Its ability to differentiate between different types of knee injuries improves the accuracy and reliability of diagnoses, ultimately assisting in the development of more effective treatment plans in clinical environments.

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The ensemble model architecture combines three distinct convolutional neural network (CNN) architectures: MobileNetV2, AlexNet, and ResNet50. Each of these architectures contributes unique features and capabilities to the ensemble, enhancing its overall performance and robustness in image classification tasks.

1. MOBILENET

Our knee osteoarthritis detection method is built on top of MobileNet, a convolutional neural network optimised for performance on mobile and edge devices. This network, which was created in 2017 by Howard et al., puts computational efficiency first without sacrificing performance. Using depthwise separable convolutions, MobileNet achieves a lightweight design with a depth of 28 layers. Because of this innovation, there are a lot less factors in the model, which makes it ideal for use in contexts with limited resources.

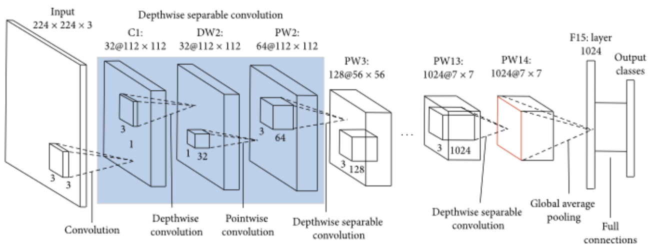

Figure 3: MobileNet Architecture

By fine-tuning, MobileNet—which was trained via transfer learning on a carefully selected dataset of knee X-ray ages—adapts to different degrees of osteoarthritis severity. Standard criteria like accuracy, precision, recall, and F1 score are used to assess the model's performance, giving rise to a thorough evaluation of its efficacy. Particularly for real-time processing of knee X-ray images in clinical settings with restricted computational resources, MobileNet's small size adds to its appeal.

Due to its high computing efficiency, MobileNet can be used to improve knee-related pathology diagnosis processes. To summarise, our system for detecting osteoarthritis in the knee has been enhanced by using MobileNet, which shows how lightweight architectures may be utilised to analyse medical images reliably and efficiently, hence improving diagnostic capabilities.

2. ALEXNET

The accuracy and effectiveness of our knee osteoarthritis diagnosis system have been improved with the addition of AlexNet, a cutting-edge convolutional neural network. The ImageNet Large Scale Visual Recognition Challenge was where AlexNet rose to popularity, which was developed in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton.

Rectified linear units (ReLU) and local response normalisation are two of AlexNet's architectural features that set it apart from other networks with a substantial depth of eight layers. Complex features that are essential for image classification applications can be extracted thanks to this deep architecture.

The AlexNet-enhanced model is trained on a variety of knee X-ray images and then goes through transfer learning and fine-tuning to adjust to the subtleties of osteoarthritis identification. The dataset's wide range of severity levels guarantees that the model can correctly classify diverse knee diseases. Standard metrics including accuracy, precision, r 3ecall, and F1 score are used in performance evaluation to give a thorough grasp of the model's diagnostic capabilities. Because of its capacity to classify images and its flexibility when it comes to medical imaging, AlexNet can be a useful tool for diagnosing osteoarthritis in the knee.

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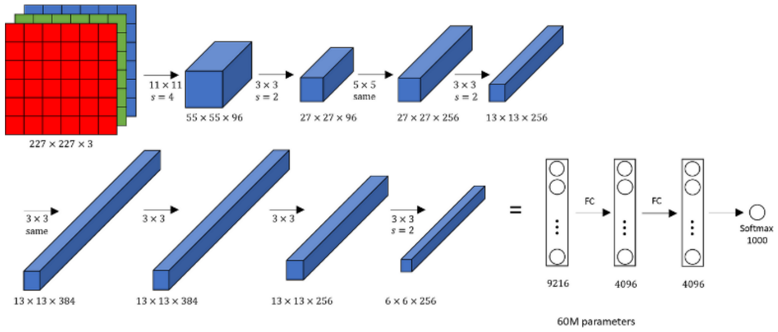

Figure 4: AlexNet Architecture

Despite not being as light as other more recent architectures, AlexNet's strong features and track record of performance make it important for medical image analysis. AlexNet's ability to improve diagnostic precision and progress the field of knee-related pathology identification is demonstrated by its inclusion into our system.

3. ResNet :

ResNet50 is a deep convolutional neural network (CNN) architecture renowned for its pioneering introduction of residual connections, which revolutionized the training of extremely deep networks. Comprising a total of 50 layers, ResNet50 design includes residual blocks that incorporate skip connections. These skip connections enable gradients to propagate more efficiently during training by circumventing the vanishing gradient problem, which often hampers the training of deep networks.

A distinctive feature of ResNet50 is its utilization of bottleneck blocks, strategically structured to enhance computational efficiency. These bottleneck blocks begin with 1x1 convolutions that reduce the dimensionality of the feature maps, followed by 3x3 convolutions to capture and process spatial information. This design choice not only reduces computational costs but also facilitates the training of deeper networks by effectively managing the flow of information through the network layers.

By incorporating residual connections and bottleneck blocks, ResNet50 achieves remarkable performance in various computer vision tasks, surpassing previous architectures in terms of accuracy and scalability. Its ability to mitigate the challenges associated with training deep networks has made ResNet50 a cornerstone in the field of deep learning, inspiring subsequent advancements in CNN architecture design and training methodologies.

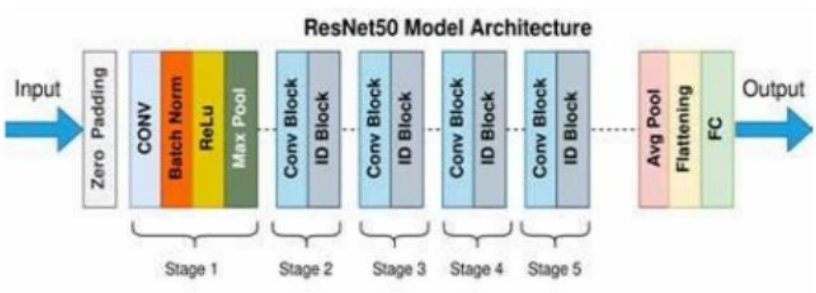

Figure 5: ResNet Architecture

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C. PROPOSED SOLUTION

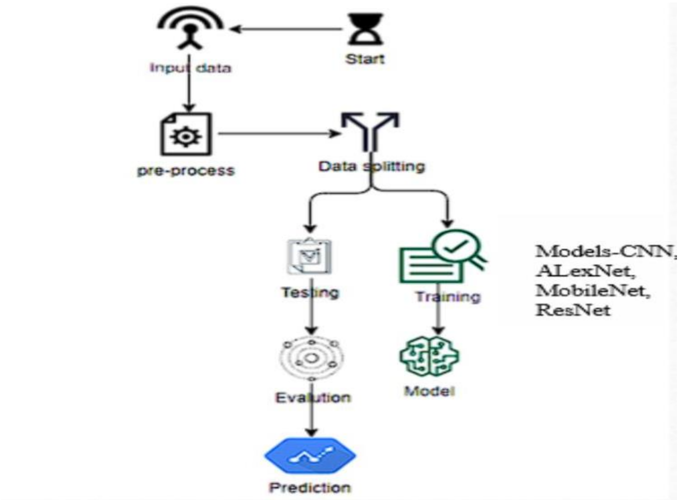

Figure 6: System Architecture

The process of developing a deep learning model for detecting knee injuries involves several stages, beginning with gathering data and concluding with generating predictions.

1. Data Collection: To develop a deep learning model for knee injury diagnosis, a representative and diversified collection of knee X-ray images must be gathered. Hospitals, medical imaging repositories, research databases, and other sources may provide these images. To train a robust model, it is imperative to make sure that the dataset includes a broad variety of knee injury types and severities.
2. Data Preparation: Before training, the collected dataset undergoes a preprocessing phase to ensure it's primed for the task. This stage may involve eliminating noise or artifacts, normalizing pixel values, and scaling images uniformly. Moreover, to enrich the dataset's variety and boost the model's ability to generalize, techniques such as rotating. flipping, and zooming could be applied for data augmentation.
➢ 3. Data Partitioning: The dataset is divided into three distinct sets after preprocessing: preparing. approval, and testing. The approval set is used to verify execution and adjust hyper-parameters, whereas the preparation set is used to create the profound learning model. Surveying the final display of the produced model is done using the testing set, which is maintained apart from the preparation interaction.
➢
➢ 4. Model Construction: When the information is ready, the accompanying step includes planning the engineering of the profound learning model. This incorporates choosing the suitable model, like Convolutional Neural Network (CNN) and designing the different layers including convolutional, pooling, and fully connected layers. The decision of engineering is directed by the intricacy of the assignment and the quality of the dataset.
➢
The training phase includes using a dataset to instruct the model once its construction has been characterised. During this stage, the calculation figures out how to extract significant features form knee X-ray images and anticipate the presence and seriousness of knee wound.

➢ 5. Evaluation and Validation: Following the training phase, the model's viability is checked utilizing an approval dataset, which helps in evaluating its capacity to order knee wounds. Measurements like accuracy, precision, recall and F1-score are used to decide the model's characterization. Based on the outcomes from the validation phase, adjustments to the model's hyperparameters can be made to further enhance its performance.
➢
➢ 6. Prediction: After the completion of training and validation, the model becomes equipped to analyse knee X-ray images that it has not seen before. When presented with these images, the trained model produces evaluations regarding the existence and extent of knee severity. Healthcare providers can utilize these insights to assist in diagnosing conditions and devising appropriate treatment plans.

Ensuring the reliability of deep learning model's predictions for clinical applications requires maintaining transparency, reproducibility, and adherence to ethical standards throughout the process.

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IV. RESULTS AND DISCUSSIONS

In this section, we present the results of our ensemble integration approach, combining the outputs of three distinct architectures for image classification tasks. Firstly, we analyse the performance of the ensemble model through output graphs, depicting the training and validation accuracy, as well as loss curves over epochs. These graphs provide insights into the learning dynamics and convergence behaviour of the model, demonstrating the effectiveness of our training strategy and highlighting any potential overfitting or underfitting issues.

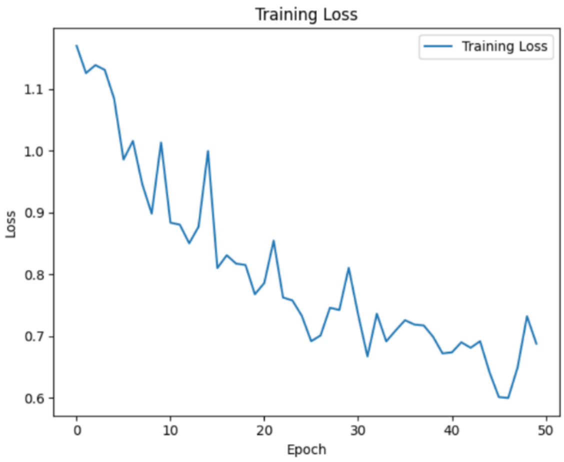

Figure 7: loss

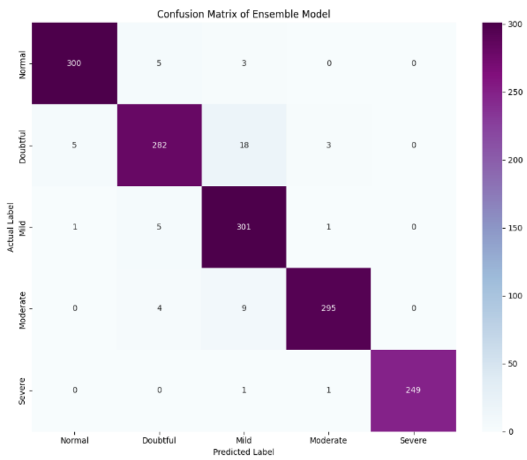

Figure 8: Confusion Matrix

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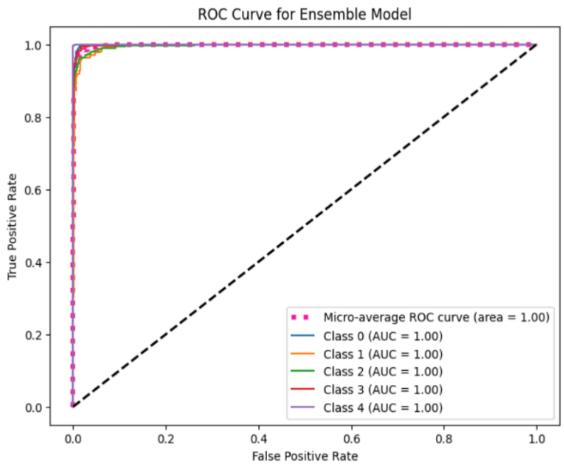

Figure 10: ROC - AUC

Figure 9: Confusion matrix

TABLE 2. Performance of ensemble models overall and across different grades.

Metric	Model	Overall	Grade				
			0	**1**	**2**	**3**	**4**
Accuracy	**ENSEMBLE**	0.96	0.97	0.92	0.98	0.96	0.99
Precision		0.96	0.98	0.95	0.91	0.98	1.0
Recall		0.96	0.97	0.92	0.98	0.96	0.99
F1-Score		0.96	0.98	0.93	0.94	0.97	1.0
AUC		1.0	1.0	1.0	1.0	1.0	1.0

TABLE 3. Cohen kappa, MAE, and MSE for ensemble model.

Metric	Ensemble Model
Weighted Kappa	0.98
MAE	0.0459
MSE	0.0620

The ensemble integration approved to be effective in enhancing the classification performance. By leveraging the complementary strengths of multiple models, the ensemble achieved an improved robustness and generalization capabilities. The high accuracy (96%) attained by the ensemble model underscores its efficacy in accurately categorising input images across diverse classes. These results highlight the potential of ensemble methods in enhancing the performance of deep learning models for image classification tasks. Further research could explore additional fusion strategies and ensemble architectures to push the boundaries of classification accuracy and address real-world challenges in image analysis and recognition.

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V. CONCLUSION

In summarizing, the utilization of advanced learning techniques, notably AlexNet, MobileNet, and ResNet, demonstrates a strong commitment to advancing the detection of knee injuries in X-ray assessments. Despite achieving commendable accuracy in predictions, persistent challenges such as imbalanced data, speculation issues, and a lack of comprehensive classification studies remain. Addressing these challenges through enhanced deployment methods and strategic adjustments is crucial to bolster the reliability and effectiveness of deep learning models in clinically diagnosing knee injuries. Besides, coordinating highlights for adaptability and lightweight arrangement is fundamental to work with the far and wide acknowledgment of these models in clinical settings. Future examination attempts ought to focus on conquering these impediments to completely saddle the capability of profound learning in altering knee injury finding. in this manner propelling patient consideration and treatment results in muscular medication**.**

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