2024 4th Int. Conf. on Innovations in Science, Engineering and Technology (ICISET)
26-27 October 2024, Chittagong, Bangladesh

2024 International Conference on Innovations in Science, Engineering and Technology (ICISET) | 979-8-3503-5549-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICISET62123.2024.10941130

Enhanced Osteoarthritis Classification through Transfer Learning and Hyperparameter-Tuned Multi-Layer Ensemble Models

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***Abstract*—Knee osteoarthritis (OA) significantly limits activity and causes physical disability in older adults. Early classification of OA is crucial to slowing its progression. This paper introduces a method for OA classification using a transfer learning fusion network with hyperparameter tuning and a Multi-Layer Ensemble approach. The process begins by balancing the dataset through data augmentation and then integrates a pre-trained model with a customized CNN model. The architecture includes four convolutional blocks with varying filter sizes (32, 64, 128, and 256), dropout layers (0.1, 0.3, 0.5, and 0.7), and Mish activation functions. The flattened output of the last MaxPool2D layer is fed into three fully connected layers (256, 128, and 5 neurons) with Softmax activation for multi-class prediction. The performance of various models is combined through a Multi-Layer Ensemble, resulting in superior performance with 75.73% accuracy. Our proposed method achieves a well-performing model for OA classification and overcomes prior limitations, emphasizing the importance of automated knee OA classification and providing an effective solution.**

***Index Terms*—Knee Osteoarthritis (OA) Classification, Transfer Learning Fusion (TLF), Machine Learning (ML) and Multi-Layer Ensemble (MLE).**

I. Introduction

Research on osteoarthritis (OA) pathology has been crucial due to its substantial economic impact, causing disability, and pain, and affecting the patient's lifestyle. OA involves more than just anatomical and physiological changes, extending to cellular stress and the degradation of the cartilage matrix [1]. Generally, OA is associated with aging. However, there are other risk factors namely obesity, lack of exercise, genetic predisposition, bone density, occupational injury, trauma, and gender [2], [3]. OA affects nearly 240 million people worldwide [4]. According to the World Health Organization (WHO), by 2050, approximately 20% of the world's population will be over 60 years old. Of that percentage, 15% will have symptomatic OA, and one-third of these people will be severely disabled [1] to [4]. Knee Osteoarthritis (KOA) is the most prevalent type, especially in older adults, leading to symptoms like chronic pain, stiffness, muscle weakness, and difficulty in daily activities [5]. Current OA diagnosis relies on physical examination and imaging techniques like X-rays, MRI scans, and arthroscopy. Efficient automatic knee OA detection is crucial to address these challenges.

Our paper structure is as follows: Section II reviews the literature. Section III provides an overview of the dataset, and Sections IV-A to IV-C detail our research approach, data preprocessing, Proposed Transfer Learning (TL) Architecture, and Justification of Our Procedural Architecture. Section V analyzes experimental results, while Sections V-B to V-C delve into Evaluation Metrics, Experimental Setup, Result Assessment. Sections VI and VII contain discussions, comparisons, and considerations of potential result validity threats. Finally, Section VIII summarizes findings, and in Section IX, we suggest future research directions, followed by references.

II. Literature Review

Several research endeavors have employed a variety of models in their investigations. For example, Christos Kokkotis et al [6] incorporated Support Vector Machines in their research. Specific studies utilized Convolutional Neural Network (CNN) models referenced by [3], [7], and [2]. Meanwhile, Joseph Humberto Cueva et al. [8] and Bofei Zhang et al. [9] applied the ResNet model. Pingjun Chen et al. [3] employed a combination of VGG-19, CNN, YOLOv2, Inceptionv3, ResNet, and DenseNet. Conversely, Jean Baptiste Schiratti et al. [10] chose EfcientNet-B0.Christos Kokkotis et al [6] reported a 74.07% accuracy in knee OA detection using SVM. Generally ML model has lower computational requirements compared to deep learning. Deep learning, with its ability to automatically learn representations from data, has achieved remarkable success in various complex tasks. Pingjun Chen et al. [3] attained a 69.7% accuracy employing VGG-19. Other models, like CNN, YOLOv2, Inceptionv3, ResNet and DenseNet. Good interpretability but comparatively low accuracy. Kevin A. Thomas et al. achieved an accuracy of 71.00% using CNN. Provide good performance but used complex model and less no of data. Aleksei Tiulpin et al. [2] employed CNN to achieve a 66.71% accuracy in knee OA. Comparatively low accuracy and training their proposed model only for the right knee persists as a limitation. Joseph Humberto Cueva et al. [8] achieved 61.00% accuracy using ResNet. Comparatively low performance and unable to emphasize the important region are the main drawbacks. [7] Bofei Zhang et al. Jean Baptiste Schiratti et al. [10] employed the EfcientNet-B0 model, with

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achieving classification rates of 72.00%. Cumulatively, these investigations provide valuable perspectives and approaches for the identification and classification of knee OA, making substantial contributions to progress in environmental management. Literature review briefly explain in Table IV

III. Dataset Description

The summary of our ”Knee Osteoarthritis” is conveniently presented in Table I and II, which can be easily accessed on Kaggle [11]. Furthermore, Figure 1 provides a visual representation of the dataset’s distribution across various classes. The dataset exhibits an imbalance in its distribution of data. This dataset contains knee X-ray data for both knee joint detection and knee KL grading. The Grade descriptions are as follows:

TABLE I
Summary of the dataset

No of Images	**Format**	**No of Classes**	**Source**
9786	PNG	5	kaggle.com

TABLE II
Number of images per class

Classes	No Of Images	Classes	No Of Images
Grade 0	2286	Grade 3	757
Grade 1	1046	Grade 4	173
Grade 2	1516		

- Grade 0: Healthy knee image.
- Grade 1 (Doubtful): Doubtful joint narrowing with possible osteophytic lipping.
- Grade 2 (Minimal): Definite presence of osteophytes and possible joint space narrowing.
- Grade 3 (Moderate): Multiple osteophytes, definite joint space narrowing, with mild sclerosis.
- Grade 4 (Severe): Large osteophytes, significant joint narrowing, and severe sclerosis.

IV. Methodology

The process begins by obtaining the dataset and performing the necessary preprocessing. ”Transfer Learning Fusion (TLF)” includes feeding images into pre-trained models, and adjusting tensors. The structure consists of four convolution blocks with different kernel sizes (5x5, 3x3, 1x1), filters (32, 64, 128, and 256), Dropout layer, ’BatchNormalization,’ MaxPooling2D with mish activation. The final output, obtained through max-pooling, is flattened and passes through three dense layers with Softmax activation for predicting class probabilities. The addition of a ’Multi-Layer Ensemble (MLE)’ for predictions involves Majority Voting, Softmax Averaging, and Weighted Averaging. The process is outlined in Figure 3.

The workflow of our research is illustrated in Figure 2.

A. Data Preprocessing

Images are cleaned, resized, and normalized during preprocessing to ensure uniformity and lower noise. There are existing training, testing, and validation sets within the dataset. In order to address unequal class distribution and ensure efficient training and model evaluation, data augmentation is employed. By adding more training examples, it grows the dataset and facilitates the model’s comprehension of new data. Nevertheless, there are drawbacks, such as the possibility that the model will become overly particular to added data and higher processing demands.

B. Architecture of Proposed Transfer Learning (TL)

Our approach starts by feeding images into pre-trained models (such as DenseNet, MobileNet, and VGG16), followed by reshaping tensors for fine-tuning. We then use four convolutional blocks (CBs) with 32, 64, 128, and 256 filters. Each block contains three convolutional layers with varying kernel sizes (5x5, 3x3, and 1x1). Additionally, a dropout layer is applied between two convolutional layers to mitigate overfitting, while BatchNormalization is used to stabilize the training process and improve the model’s generalization ability. MaxPooling2D layers are placed between the convolutional blocks to reduce the dimensionality of the feature maps. The output is then flattened, converting the multi-dimensional data into a 1D array. This flattened output from the final max-pooling layer is passed through three dense layers with 256, 128, and 5 neurons, respectively. Finally, Softmax activation is employed in the last layer to predict multiclass probabilities (Figure 3). To enhance overall performance, we introduced a Multi-Layer Ensemble (MLE). In the first prediction stage, MLE employed Majority Voting (MV), Softmax Averaging (SAvg), and Weighted Averaging (WAvg), with the best-performing method progressing to higher ensemble tiers [12]. However, in the second and third layers of the ensemble, only Weighted Averaging (WAvg) was used. As a result, we achieved better performance compared to previous methods (Figure 4).

C. Justification of Our Procedural Architecture

In CNN, batch normalization addresses internal covariate shifts, maintaining a consistent input distribution for each layer during training. This expedites training, promotes stable convergence, and enhances overall performance. The superior performance of our model, compared to the previous task, is attributed to its architecture, where the Multi-Layer Ensemble approach seamlessly amalgamates architectural strengths, leading to a notable improvement in prediction accuracy.

V. Performance Analysis

A. Evaluation Measures

We utilized diverse metrics, such as accuracy, precision, recall (sensitivity), f1-score, specificity, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC), to assess the efficacy of the model. The mathematical formulations for these metrics are provided below [13], [14].

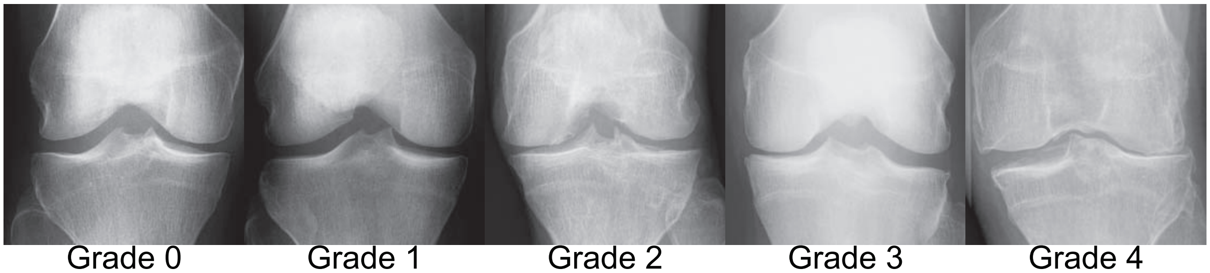

Fig. 1. Sample images for each class

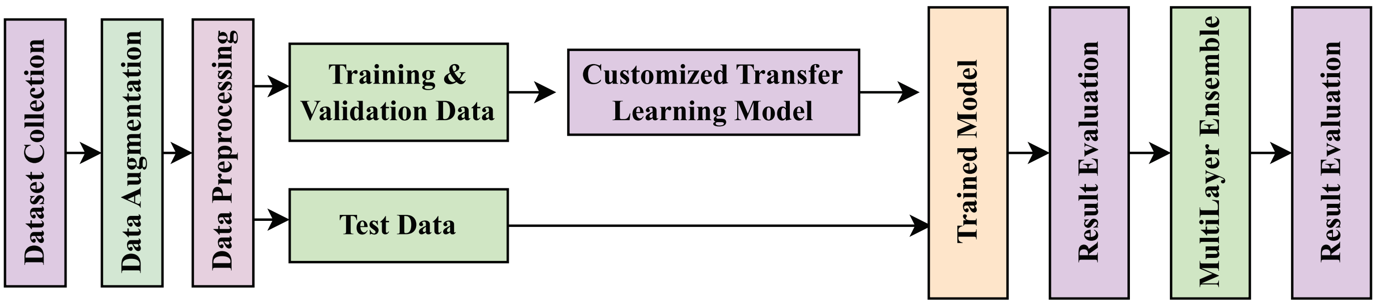

Fig. 2. Sequential workflow of the proposed methodology

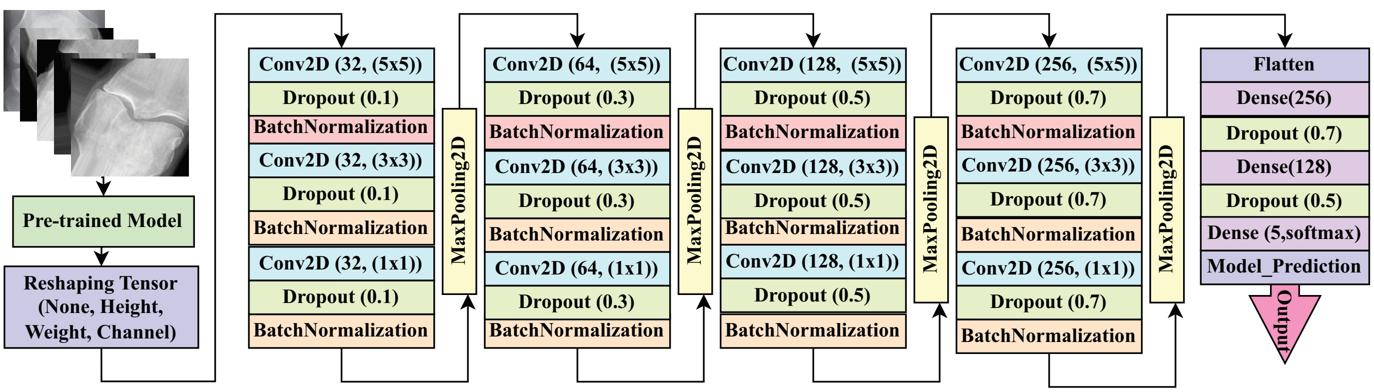

Fig. 3. Architectural view of the proposed methodology

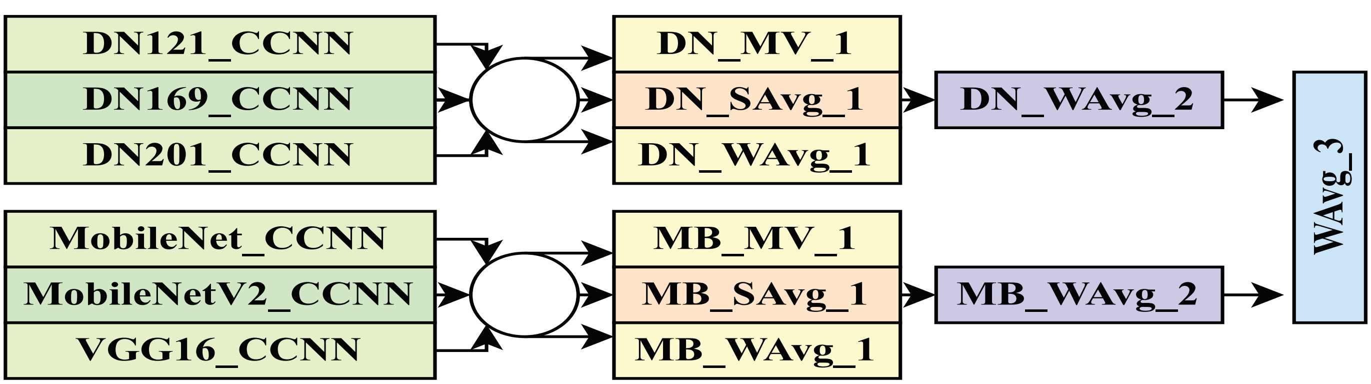

Fig. 4. Multi-Layer Ensemble Approach

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

The model's capacity to minimize false positives is measured by precision, recall examines how well it captures true positives, F1-score combines precision and recall, and specificity analyzes how well it can decrease false negatives. Accuracy checks overall accuracy. The True Positive (TP): Correctly predicted positive cases where the condition is present, True Negative (TN): Correctly predicted negative cases where the condition is absent, False Positive (FP): Incorrectly predicted positive cases (Type I error), and False Negative (FN): Incorrectly predicted negative cases (Type II error).

B. Experimental setup

An Intel Xeon CPU with two cores (690 ms/step) and a GPU P100 were used for architectural operations on Kaggle. Images entered were measured (224,224,3). In order to meet our requirements and get rid of overfitting problems, models go through various amounts of epochs. batch size 16) using the Adam optimizer (categorical cross-entropy loss, lr: 0.005). Reduce was used to stop early on the Plateau (patience: 10).

C. Results Assessment

Table III showcases the results of our TLF architectures and MLE methods. Notably, the inclusion of the TLF model significantly boosts performance across various metrics.

In this work, three basic architectures were utilized: DenseNet, MobileNet, and VGG16. Two variations of MobileNet, MobileNet and MobileNetV2, as well as three variants of DenseNet—DenseNet121, DenseNet169, and DenseNet201—were examined. Since VGG16 is unique, there were no other variations. A customized CNN model was seamlessly integrated with each architecture. The DenseNet-based models performed exceptionally well, with accuracy rates of 71.42% for MobileNet and 73.07% for DenseNet121. However, among all the proposed models, VGG16 had the lowest performance, with an accuracy of 71.12%. The MobileNet-based model outperformed VGG16. The DenseNet-based model's first-layer ensemble improved accuracy to 74.72% for MV, 74.72% for SAvg, and 74.95% for WAvg. After the first-layer ensemble, the second-layer ensemble's WAvg improved to 74.95%. Although the second-layer ensemble for the MobileNet-based model increased accuracy to 74.14%, its first-layer ensemble performance was worse than that of the DenseNet-based model. Accuracy reached 75.73% with

TABLE III
PERFORMANCE ANALYSIS ON TEST DATA

Algorithm	Accuracy %	Precission%	Recall%	F1-score%
DN121-CCNN	73.07	73.29	73.07	72.61
DN169-CCNN	72.19	71.92	72.19	71.69
DN201-CCNN	71.54	70.98	71.54	70.46
DN_MV_1	74.72	74.45	74.72	74.03
DN_Savg_1	74.72	74.45	74.72	74.03
DN_Wavg_1	74.95	74.92	74.95	74.31
DN_Wavg-2	74.95	74.92	74.95	74.31
MobileNet _CCNN	72.42	72.86	72.42	71.62
MobileNetV2 _CCNN	71.51	72.33	71.51	70.52
Vgg16_CCNN	71.12	72.23	71.12	70.16
MB_MV_1	73.84	74.81	73.84	73.05
MB_Savg_1	73.84	74.81	73.84	73.05
MB_Wavg_1	74.14	75.03	74.14	73.36
MB_Wavg-2	74.14	75.03	74.14	73.36
Wavg-3	75.73	75.88	75.73	74.87

Note: Gradually 1,2 and 3 means 1st, 2nd and 3rd layer Enssemble.

a third-layer ensemble, which combined the two top WAvg models. Specifically, we observe that DenseNet121 achieves the highest training and validation accuracy among all models. Addressing this was particularly challenging due to frequent overfitting issues. To mitigate this problem, we used a higher learning rate, few number of epochs, and incorporated a dropout layer to reduce model complexity. While fewer convolutional blocks could have been used, we prioritized performance, which is why we employed four convolutional layers along with the dropout layer. Figure 5 shows the confusion matrix of the final model, consistent with the findings.

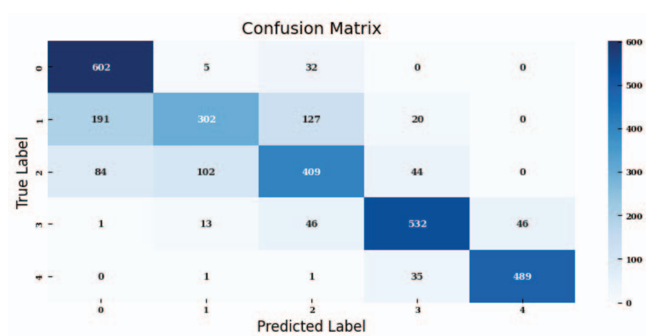

Fig. 5. Confusion Matrix of the proposed model

VI. Discussion and Extended Comparison

Table IV now shows a detailed comparison, highlighting that our recent results surpass those of previous studies. It's essential to mention that although Rima Tri Wahyuningrum et al. [9] achieved a higher accuracy of 74.81% in their earlier work, they used only a small subset of the dataset and employed complex algorithms. In contrast, we worked with a dataset of 9,786 images, confirming the superiority of our model in this context. Our model, while being less complex, is advanced and user-friendly, proving its effectiveness.

TABLE IV
PERFORMANCE COMPARISON

Article	Accuracy	Precision	Recall	F1-score	Specificity
[6]	74.07	-	-	-	-
[3]	69.70	-	-	-	-
[7]	71.00	-	-	-	-
[9]	74.81	-	-	-	-
[2]	66.71	-	-	-	-
[8]	61.00	-	-	-	-
[10]	72.00	-	-	-	-
Ours	**75.73**	**75.88**	**75.73**	**74.87**	**93.73**

VII. THREATS TO VALIDITY

Although our research uses augmentation to address dataset imbalance, it is not without limits. We intend to investigate new approaches to data balance in the future. The model's deployment on mobile devices presents difficulties and could affect performance because of normalization and resizing processes. Additionally, make an effort to use improved techniques that can eliminate overfitting problems.

VIII. CONCLUSION

This paper presents a multi-layer ensemble and a hyperparameter-tuned Transfer Learning Fusion Network aimed at classifying knee osteoarthritis (OA). To make these automated methods applicable to clinical research or medical diagnosis, this study explores various approaches and challenges that need to be addressed. To enhance the model's performance, we propose integrating a pre-trained model with a custom CNN and a multi-layer ensemble. After incorporating the third-layer ensemble, our proposed method achieved an accuracy of 75.73%. The model's performance aligned with our initial expectations, and highlights the crucial role of automated knee OA classification and providing a more efficient solution.

IX. FUTURE SCOPE

For tasks like pre-processing, feature extraction, and classification, numerous approaches have been studied, but the outcomes are still far from being applied in real-world situations. Therefore, investigating cutting-edge methods may result in increased knee OA classification accuracy. We intend to extend our study in the future to incorporate automatic knee OA diagnosis and grading techniques that integrate many imaging modalities, such as X-ray with ultrasound or MRI datasets.

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