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INTEGRATING VGG RE-TRAINED FEATURE EXTRACTION WITH MACHINE LEARNING FOR KNEE OSTEOARTHRITIS SEVERITY LEVELS DETECTION USING X-RAY IMAGES

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ABSTRACT

Knee osteoarthritis, a degenerative joint disease affecting weight-bearing joints such as the knees and hips, poses substantial diagnostic hurdles due to its complicated pathophysiology and development. Traditional diagnostic methods rely heavily on clinical examinations and imaging techniques like X-rays, which can be subjective and vary with clinician experience. To overcome these problems, new advances in machine learning (ML) and deep learning (DL) offer promising alternatives for improving the accuracy of knee osteoarthritis identification. This study proposes a novel methodology that combines retrained VGG models with various machine learning techniques. The Knee Osteoarthritis Dataset with Severity Grading is preprocessed, and features are extracted using fine-tuned VGG16 and VGG19 models. A number of machine learning models, including Naive Bayes, K-Nearest Neighbors, Decision Tree, Random Forest, Bagging, and AdaBoost, are then trained using these extracted characteristics. These models' performance is assessed using metrics including F1-score, recall, accuracy, and precision. The results reveal that the combination of VGG19 with fine-tuning and Random Forest achieves the best performance, with an impressive accuracy of 62.68%. This approach significantly improves diagnostic accuracy and holds potential for enhancing clinical decision-making and management of knee osteoarthritis, offering a robust tool for early detection and personalized treatment strategies.

I. INTRODUCTION

Weight-bearing joints, including the knees and hips, are susceptible to the complex illness known as osteoarthritis (OA). Significantly contributing factors to its etiology include advanced age, high body mass index (BMI), and joint malalignment [1]. OA is a common type of arthritis that produces severe pain, stiffness, and swelling in the affected joints. Knee osteoarthritis in particular is one of the commonest forms of arthritis [2].

Knee osteoarthritis (KOA) is a slowly progressive disease that involves the degradation of cartilage, remodeling of bone, and inflammation [3]. The knee is the joint in the human body most commonly afflicted by this most prevalent musculoskeletal degenerative disease [4]. Pathologically, KOA is defined by a number of structural alterations in the knee joint, such as the development of osteophytes, inflammation of the synovium, subchondral sclerosis, and erosion of cartilage [5].

The impact of knee osteoarthritis extends beyond physical discomfort, as it is associated with a 35-37% increased risk of reduced time-to-mortality, primarily driven by pain [6]. Furthermore, KOA is linked to an increased risk of all-cause mortality, with disability and deteriorations in quality of life being significant contributors [7]. Early and accurate detection is essential for effective treatment and management of knee osteoarthritis because of the significant impact it has on an individual's health and quality of life. Imaging tools like X-rays and clinical examinations play a major role in traditional diagnostic methods. However, a clinician's experience and subjective judgment may have a role in how X-ray pictures are interpreted. Recent developments in artificial intelligence, notably in machine learning and deep learning, present intriguing answers to these problems. Modern developments in deep learning (DL) and machine learning (ML) have greatly improved the ability to identify and categorize knee osteoarthritis (OA) from medical imaging, especially X-ray pictures. Numerous research works have exhibited the effectiveness of these computational techniques in enhancing clinical results and diagnostic precision.

Attaining state-of-the-art performance in knee osteoarthritis severity classification from X-ray images has been demonstrated by machine learning techniques, such as logistic regression [8]. These algorithms can handle large datasets and identify patterns that are often indistinguishable to the human eye, providing a robust tool for medical diagnostics. Deep convolutional neural networks (CNNs), a subset of machine learning models, have been particularly effective in detecting patellofemoral osteoarthritis from knee radiographs. Studies have demonstrated that CNN-based models outperform conventional reference models, offering higher accuracy and reliability [9]. Medical image analysis benefits greatly from CNNs' capacity to automatically learn and extract characteristics from unprocessed input.

Furthermore, machine learning methods, especially CNN networks, can enhance the diagnosis of knee osteoarthritis by analyzing real-world X-ray imaging data. These models reduce the workload for doctors by providing automated and precise diagnostic suggestions, thus facilitating more efficient clinical workflows [10]. Enhancing patient outcomes might be greatly increased by using these cutting-edge computational tools into clinical practice. Deep learning techniques also play a crucial role in the early detection of osteoarthritis. By accurately identifying the disease at its initial stages, these methods can help prevent further cartilage damage and bone injury, thereby enabling timely and effective interventions [11]. Early diagnosis is essential for managing OA, as it can significantly slow disease progression and improve the quality of life for patients.

Clinical diagnoses have been improved and necessary medical interventions have been expedited by the use of machine learning in the early diagnosis and prediction of knee osteoarthritis. Machine learning models, including deep neural networks, have been shown to enhance clinical decision-making processes, providing clinicians with valuable insights derived from complex data [12]. This capability underscores the transformative potential of machine learning in healthcare.

According to utilized Deep Siamese CNN combined with ResNet-34 for the detection and classification of knee OA severity. This study employed the dataset from [13] along with a private hospital dataset for validation, achieving a balanced accuracy of 61.0%. Although this method demonstrated good performance, the slight difference in accuracy compared to the proposed method suggests that the choice of classifier and precise tuning can significantly enhance performance [14].

Nurmirinta et al. implemented a two-stage classification approach using Balanced Random Forest and MRI features, resulting in a higher balanced accuracy of 65.9%. This approach benefited from the detailed and high-resolution MRI data, which provide more comprehensive insights into knee joint structures compared to X-ray images [15]. According to adopted a CNN-based automatic detection approach with image processing techniques and MRI images, achieving a balanced accuracy of 61.0%. Into Cueva et al., this result underscores the importance of dataset composition and model architecture in influencing outcomes [16].

The Osteo-NeT system, which uses sequential convolutional neural network-based transfer learning models to identify knee osteoarthritis from X-ray images, is one prominent example. Predictive accuracy has increased with this system, and the pretrained VGG-16 model has proven to be the most effective [17]. Transfer learning allows models to leverage knowledge from previously trained networks, enhancing their performance on new, related tasks and reducing the need for extensive labeled datasets.

The present study aims to explore the potential of VGG re-trained feature extraction in enhancing the detection and classification of knee osteoarthritis using X-ray pictures. This is based on the encouraging findings of previous research, which suggest integrating it with different machine learning techniques. By leveraging the strengths of both deep learning and traditional machine learning techniques, this proposed approach aims to develop a diagnostic tool that could potentially assist clinicians in the early detection and effective management of knee osteoarthritis.

II. METHODOLOGY

II.1 DATASET

The dataset utilized in this study, known as the "Knee Osteoarthritis Dataset with Severity Grading," sourced from [13], [18], is tailored for knee osteoarthritis (OA) detection and severity grading through X-ray images. Comprising 8,260 X-ray images, the dataset provides a comprehensive representation of knee conditions across various severity levels. According to the Kellgren-Lawrence (KL) grading system, these images are categorized into five grades: Grade 0, which denotes a healthy knee image, and Grade 4, which denotes significant osteoarthritis. The following is how the pictures are distributed by grade: Grade 0 comprises 3,253 images, Grade 1 includes 1,495 images, Grade 2 consists of 2,175 images, Grade 3 encompasses 1,086 images, and Grade 4 contains 251 images. Each grade signifies distinct pathological changes in the knee joint, including osteophyte formation, joint space narrowing, and sclerosis, providing valuable insights for diagnostic and prognostic purposes.

This diverse representation allows for the exploration of the entire spectrum of knee OA severity, enabling comprehensive model training and evaluation. Moreover, the dataset is partitioned into three subsets—training, validation, and testing—with respective proportions of 70%, 10%, and 20%. This partitioning strategy ensures the robustness and generalizability of developed machine learning models by facilitating thorough model tuning and validation on unseen data.

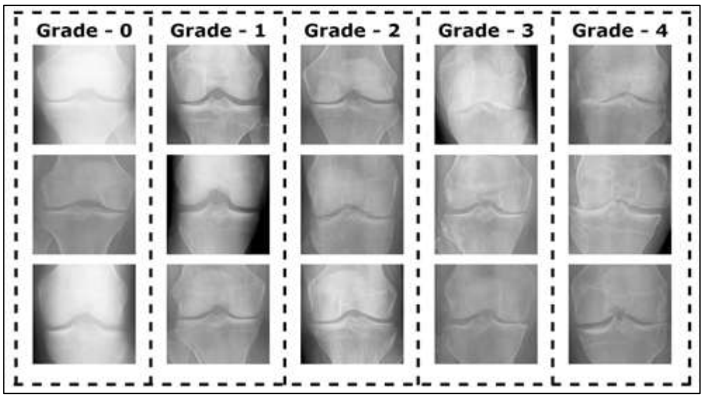

Figure 1: Example of X-ray images illustrating knee OA severity levels.
Source: Authors, (2025).

Figure 1 depicts sample images from the dataset used in this research, showcasing the variations in knee OA severity captured in the X-ray images. Overall, the "Knee Osteoarthritis Dataset with Severity Grading" serves as a valuable resource for advancing research in knee OA diagnosis and management through computational methods, enabling researchers to develop and evaluate machine learning models for accurate and reliable knee OA detection, ultimately contributing to improved patient care and outcomes in clinical practice.

II.2 PROPOSED METHOD

The proposed methodology adopts a multi-step approach integrating deep learning and traditional machine learning techniques for knee osteoarthritis (OA) detection from X-ray images. Initially, the Knee Osteoarthritis Dataset with Severity Grading undergoes preprocessing, including resizing each X-ray image to 224x224x3 dimensions. This step enhances the images for subsequent feature extraction and model training processes without further partitioning into training, validation, and testing sets. The feature extraction phase, pretrained VGG16 and VGG19 models, initialized with weights trained on ImageNet, are utilized to extract deep features from the X-ray images. These models are fine-tuned on the knee osteoarthritis dataset to adapt to its specific characteristics, enhancing their feature representation capabilities. Subsequently, the classifier heads of the pretrained VGG models are removed, and the extracted features are integrated into the pipeline.

Following the feature extraction, various machine learning models, including Naive Bayes, K-Nearest Neighbors (KNN) with different values of K (1, 3, 5), Decision Tree, Random Forest, Bagging, and AdaBoost, are trained on the extracted features. These models learn patterns and relationships between the features and the corresponding knee OA severity grades, facilitating effective detection.

The performance evaluation of the developed models employs commonly used metrics such as accuracy, precision, recall, and F1-score. The evaluation is conducted solely on the validation set to fine-tune hyperparameters and optimize model performance. Finally, the best-performing models are assessed on the testing set to evaluate their generalization ability and robustness, aiming to develop an effective diagnostic tool for knee osteoarthritis detection using X-ray images, thereby providing valuable insights for clinical practice. The proposed configuration can be seen in Figure 2.

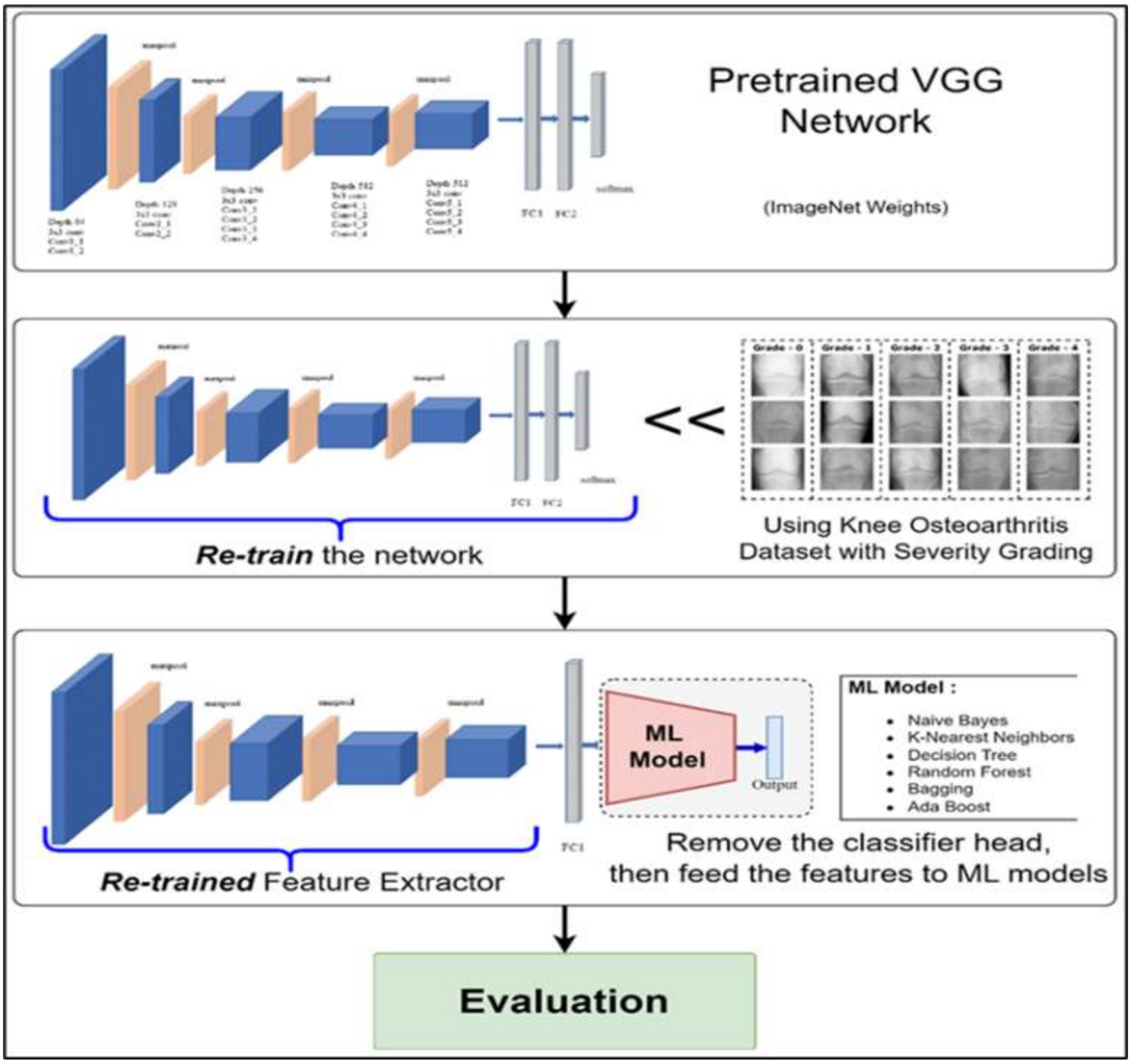

Figure 2: Proposed configuration (Integrating VGG Re-trained Feature Extraction with Machine Learning).
Source: Authors, (2025).

II.3 CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) are pivotal in computer vision, renowned for their proficiency in recognizing visual patterns within image data. Pretrained CNN models, trained extensively on datasets like the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), exhibit exceptional adaptability and precision in identifying diverse objects. Through transfer learning, these models can be repurposed for various tasks, expediting development and deployment. CNNs integrate feature extraction and classification, discerning intricate patterns from images with robust adaptability to variations.

Convolution procedures are used by the Convolutional Neural Network (CNN) to extract features from the input pictures. The convolution operation between a kernel $\boldsymbol{K}$ and a input image $\boldsymbol{I}$ is mathematically defined as:

$$(I * K)(x, y) = \sum_{m}\sum_{n} \boldsymbol{I}(m, n) \cdot \boldsymbol{K}(x - m, y - n) \tag{1}$$

where $\boldsymbol{I}(m, n)$ represents the pixel value at position (m,n)(m, n)(m,n) in the input image, and $\boldsymbol{K}(x - m, y - n)$ represents the kernel value. Pooling operations, which follow convolution, reduce the spatial dimensions by taking the maximum or average values within a specified window, enhancing the network's ability to capture spatial hierarchies in the data. Foundational layers like Convolution and Pooling progressively extract hierarchical features, enhancing efficacy across tasks, facilitating nuanced analysis of visual data [19], [20].

II.4 VGG

Deeper and more complex networks are being developed in Convolutional Neural Network (CNN)-based model building in an effort to achieve higher detection accuracy, and VGG is an example of this strategy. The winning team in the 2014 ILSVRC challenge, Simonyan and Zisserman, demonstrated a significant breakthrough by using only modest 3x3 convolutional filters and expanding the depth of the convolutional block to include 16–19 convolutional layers.

The VGG16 architecture consists of five maximum pooling layers and thirteen convolutional layers, each of which has an activation function that is a rectified linear unit (RELU). The first two, each with 4096 channels, and the third, with 1,000 channels and a softmax activation function, are the three fully connected layers that comprise the categorization block [21].

The number of convolutional layers utilized in each convolutional block is what distinguishes VGG16 from VGG19. Compared to VGG16, which has thirteen convolutional layers, VGG19 has sixteen. Notably, the input picture is downscaled using 2x2 maximum pooling layers with a stride of 2, and the entire kernel size utilized in the VGG architecture is 3 x 3. Before it reaches the classification block, the downsampled and filtered image that is produced when an RGB image with dimensions of 224x224x3 is used as the standard input for the convolutional networks of VGG16 is 7x7x512.

The backpropagation approach is used to update the model's parameters during the fine-tuning stage in order to minimize the category cross-entropy loss. Frequently employed in multi-class classification issues, the categorical cross-entropy loss, or $\bar{\boldsymbol{L}}$, is defined as follows:

$$L(y, \hat{y}) = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij}) \tag{2}$$

where y_{ij} is a binary indication (0 or 1) if class label j is the proper classification for observation i, $\hat{y}_{ij}$ is the anticipated probability that observation i belongs to class j, $\boldsymbol{N}$ is the number of observations, and $\boldsymbol{C}$ is the number of classes. The weight updates during training are computed as follows:

$$W_{t+1} = W_t - \eta \frac{\partial L(W_t)}{\partial W_t} \tag{3}$$

where $\boldsymbol{W_t}$ indicates the iteration's weights $\boldsymbol{t}, \boldsymbol{\eta}$ is the learning rate, and $\frac{\partial L(W_t)}{\partial W_t}$ shows how the loss slopes in relation to the weights.

This architectural design helps to successfully integrate deep learning and conventional machine learning techniques for improved diagnostic accuracy. It also makes it possible for the VGG models to adapt to the subtleties of knee osteoarthritis detection from X-ray images. These two factors work together to optimize the VGG models' performance [22].

II.5 PERFORMANCE EVALUATION

In order to determine how effective a system is, performance evaluation is essential. This is especially true for classification tasks, where measurements such as accuracy, precision, recall, and F1-score are commonly utilized. The system's accuracy in categorizing data is assessed by the ratio of properly predicted cases to the whole dataset, which allows the system to successfully distinguish between positive and negative examples. Precision gauges the system's accuracy in precisely identifying true positive predictions. In contrast, recall measures the system's ability to correctly identify actual positive instances, crucial in scenarios where missing positive instances incurs significant costs.

The F1-score provides a comprehensive evaluation by combining precision and recall, offering a holistic assessment metric, particularly beneficial for addressing datasets with imbalanced class distributions. These metrics provide a comprehensive knowledge of a model's performance across several categorization elements, providing a full evaluation of its efficacy [23].

III. RESULTS AND DISCUSSION

This study's experimental setup made use of the Google Colab Pro platform and the Python programming language, as well as a GPU T4 with 25 GB of RAM for effective processing. Important libraries such as scikit-learn, TensorFlow, and Keras were used; these allowed access to different pre-trained architectures and weights from ImageNet, which helped with the creation and optimization of the deep learning models.

The optimization procedure was continually guided by the cross-entropy loss function throughout the tests. During the first transfer learning phase, the training protocol was designed to consist of 10 epochs with a batch size of 16 and an initial learning rate of 0.0001. To improve the performance of the model, a methodical fine-tuning approach was used, which involved unfreezing layers one at a time with an adjusted learning rate of 0.00001. The use of callbacks improved training process monitoring and control, enhancing experiment reproducibility and transparency.

Table 1: Performance Results of Proposed Models.

Base Model	Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	Base (TL)	45.954	36.591	45.954	36.125
	Base + FT	62.258	58.981	62.258	59.021
	Base + FT + NB	37.923	46.979	37.923	37.723
	Base + FT + KNN-1	53.080	53.090	53.080	52.970
	Base + FT + KNN-3	55.085	53.323	55.085	53.027
	Base + FT + KNN-5	58.394	56.412	58.394	55.903
	Base + FT + DT	50.969	51.289	50.969	51.088
	Base + FT + RF	60.775	56.196	60.775	56.190
	Base + FT + Bagging	59.843	57.793	59.843	58.281
	Base + FT + Ada Boost	51.993	46.203	51.993	47.193
VGG19	Base (TL)	45.229	35.934	45.229	35.571
	Base + FT	60.930	58.059	60.930	54.325
	Base + FT + NB	36.957	46.482	36.957	37.050
	Base + FT + KNN-1	53.200	53.075	53.200	52.858
	Base + FT + KNN-3	56.763	55.564	56.763	54.498
	Base + FT + KNN-5	58.756	57.131	58.756	55.978
	Base + FT + DT	48.853	49.079	48.853	48.950
	Base + FT + RF	**62.681**	**58.414**	**62.681**	**57.549**
	Base + FT + Bagging	58.756	55.505	58.756	56.191
	Base + FT + Ada Boost	52.899	48.045	52.899	47.894

Source: Authors, (2025).

Table 2: Comparison of Methods for Knee Osteoarthritis Detection and Classification.

urce	Method	Dataset	Number of Classes	Accuracy (%)
Our(s)	*Proposed*	Chen [13]	5	62.68
Cueva, 2022 [14]	Deep Siamese CNN + fine-tuned ResNet-34	Chen [13] + Private hospital dataset	5	61.0
Nurmirinta, 2024 [15]	Two-stage classification	multiple sources MRI images	3	65.9
Hemanth, 2023 [16]	Deep Siamese CNN + fine-tuned ResNet	N/A	5	61.0

Source: Authors, (2025).

After the fine-tuning phase, the classifier heads of the pre-trained VGG16 and VGG19 models were removed. The extracted features were then fed into various machine learning models using scikit-learn, including Naive Bayes, K-Nearest Neighbors (KNN) with different values of K (1, 3, 5), Decision Tree, Random Forest, Bagging, and AdaBoost, to enhance the detection capabilities.

The results of these experiments, including evaluations of accuracy, precision, recall, and F1-score for each model configuration, are presented in Table 1. This comprehensive approach aimed to develop an effective diagnostic tool for knee osteoarthritis detection using X-ray images, providing valuable insights for clinical practice.

The most effective model configuration, according to an examination of the performance data, is the VGG19 base model combined with Random Forest (RF) as the machine learning algorithm and fine-tuning (FT). With an astounding accuracy of 62.681%, this setup is the best-performing model out of all the configurations that were examined. Furthermore, this model exhibits balanced metrics for precision, recall, and F1-score, showing strong performance across a variety of evaluation criteria.

This configuration successfully captures the intricate patterns and correlations found in the knee osteoarthritis dataset by utilizing the re-trained features taken from the VGG19 model and the ensemble learning power of Random Forest. This model's high accuracy rate indicates that it can correctly categorize X-ray pictures into distinct severity degrees of osteoarthritis in the knee, which is useful information for clinical diagnosis and therapy choices.

The VGG19-based design is clearly the most successful in this investigation, even though other configurations, such the VGG16 base model with fine-tuning and Random Forest, which reaches an accuracy of 60.775%, also show promising performance. Its exceptional accuracy highlights how crucial model and algorithm selection are to maximizing knee osteoarthritis detection systems' diagnostic accuracy.

Overall, knee osteoarthritis can now be better identified and classified from X-ray images thanks to the suggested methodology of combining VGG re-trained feature extraction with machine learning models, especially the combination of VGG19 with fine-tuning and Random Forest. This model shows robust performance across several evaluation measures and attains the maximum accuracy, which makes it a suitable choice for practical clinical applications. Additionally, Figure 3 illustrates the confusion matrix of the best-performing model based on test data, providing further insights into its performance.

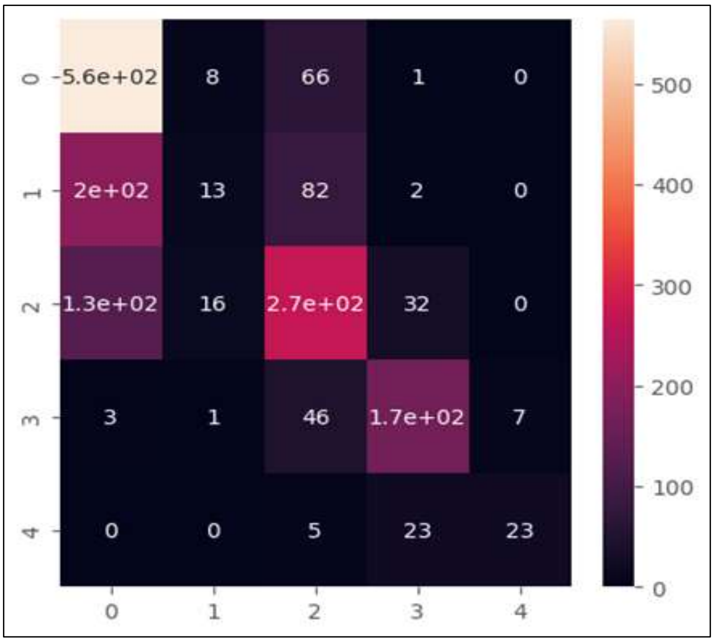

Figure 3: Confusion matrix for VGG19 + FT + RF model.
Source: Authors, (2025).

In this study, the method employed is integrating VGG re-trained feature extraction with machine learning for detecting knee osteoarthritis severity levels using X-ray images. The confusion matrix presented in the results section illustrates the distribution of correct and incorrect predictions made by the proposed model.

To provide a broader context, we compare this model's performance with other recent studies that have utilized different methodologies for the same task. The table 2 summarizes these comparisons in terms of method, dataset, number of classes, and balanced accuracy.

The proposed method, which integrates VGG re-trained feature extraction with machine learning, achieved a balanced accuracy of 62.68%. This performance indicates the model's effectiveness in accurately classifying different severity levels of knee osteoarthritis from X-ray images. The confusion matrix results further illustrate the model's robustness in handling the inherent imbalance in the dataset, reflecting a strong capability to differentiate between the classes.

Comparing this with other studies, Cueva et al. (2022)[14] utilized a Deep Siamese CNN combined with ResNet-34, achieving a balanced accuracy of 61.0%. This minor difference suggests that while the methodologies are similar, the fine-tuning of the VGG model and the choice of Random Forest as the classifier in the proposed method likely contributed to the slightly higher accuracy. Specifically, VGG19's depth and capacity for feature extraction may have allowed it to capture more nuanced patterns in the X-ray images, which, when combined with the robust ensemble learning approach of Random Forest, resulted in better overall performance.

According to[15] employed a two-stage classification approach using Balanced Random Forest and MRI features, which resulted in a higher balanced accuracy of 65.9%. This approach benefited from the detailed and high-resolution data provided by MRI images, which offer more comprehensive insights into knee joint structures compared to X-ray images. While this method shows the advantage of using more detailed imaging modalities, it also indicates that improvements could be made by integrating multiple types of imaging data in future work.

In [16] also used a CNN-based automatic detection approach with MRI images and image processing techniques, achieving a balanced accuracy of 61.0%. Similar to Cueva et al., the slightly lower accuracy compared to the proposed method highlights the potential advantages of using VGG re-trained features with a Random Forest classifier. The Random Forest's ability to handle high-dimensional data and its robustness against overfitting likely contributed to the improved performance.

Overall, the proposed method demonstrates competitive performance and provides a strong foundation for further research and development in this area. The integration of VGG19's powerful feature extraction capabilities with the ensemble learning strength of Random Forest appears to be a particularly effective combination for this application. Future improvements could involve leveraging more detailed imaging modalities or combining multiple types of data to further enhance the accuracy and robustness of knee osteoarthritis detection models.

IV. CONCLUSION

In conclusion, a viable method for improving the identification and categorization of knee osteoarthritis using X-ray pictures is the integration of VGG re-trained feature extraction with different machine learning algorithms. With an astounding accuracy of 62.681%, the VGG19 base model with fine-tuning and Random Forest combination proves to be the most successful of the evaluated combinations. Precision, recall, and F1-score are just a few of the evaluation parameters this model performs well on, highlighting its potential for precise diagnosis in clinical contexts. The findings highlight the importance of fine-tuning pre-trained models and selecting appropriate machine learning algorithms to optimize diagnostic accuracy.

For future work, integrating additional imaging modalities such as MRI could potentially improve diagnostic accuracy. Exploring advanced deep learning architectures and further fine-tuning of the model parameters could also enhance performance. Additionally, expanding the dataset with more diverse samples and including real-world clinical data would help in validating the model's applicability in practical clinical settings. These steps could lead to the development of even more accurate and reliable diagnostic tools for knee osteoarthritis detection.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Methodology: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Investigation: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Discussion of results: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Writing – Original Draft: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Writing – Review and Editing: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Resources: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah
Approval of the final text: Simeon Yuda Prasetyo and Ghinaa Zain Nabiilah

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