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Article

ULTRASOUND-BASED DEEP LEARNING SYSTEM FOR EARLY DETECTION AND RISK PREDICTION OF KNEE OSTEOARTHRITIS

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Abstract: Knee Osteoarthritis (OA) is a joint disease that makes movement difficult and reduces quality of life, especially for older people. It is caused by damage to cartilage, narrowing of joint spaces, formation of bone spurs, and stiffness in the joints. Current methods to diagnose OA include X-rays, which can be inaccurate and subjective, and MRI, which is very accurate but expensive and not widely available. To solve these problems, we propose an automated system using machine learning and image processing with ultrasound images. Ultrasound is a low-cost and non-invasive option that helps detect key OA markers like cartilage damage, joint space narrowing, and bone spurs. This system can provide early and accurate diagnosis, and personalized treatment, and reduce the workload of healthcare professionals, ultimately improving patient care and making diagnosis more consistent and efficient.
Keywords: CNN, VGG16, Deep Learning, Predictive Modelling, Risk Prediction

1. Introduction

Osteoarthritis of the knee is a common cause of pain, disability, and impaired mobility, mainly in older patients. It is a degenerative joint disease as articular cartilage gets broken down and bone changes beneath it result in increasing stiffness, swelling, and loss of function of the joint. Knee osteoarthritis is a condition found in millions worldwide, posing significant morbidity on the quality of life and assuming a huge economic burden through costs of health care and loss of productivity. Considering the increasing prevalence of knee osteoarthritis among the elderly, coupled with the unabated rise of obesity worldwide, timely and precise diagnosis should therefore be provided to have the patient optimally treated and managed.

There are two main types of knee osteoarthritis: primary and secondary. Primary osteoarthritis is the most common type of knee osteoarthritis and is usually caused by age-related wear and tear on the cartilage in the knee. Secondary osteoarthritis is a type of knee osteoarthritis caused by an injury or other direct damage to the knee joint. This can include injuries that cause inflammation in the joint, or other types of arthritis that damage the cartilage

Traditionally, a diagnosis of knee OA requires clinical evaluation, patient history, and various radiographic methods including X-rays and magnetic resonance imaging. None of them, however, is without limitation. X-rays mainly assess bone changes and are poor at visualizing soft tissues such as cartilage, ligaments, and synovium. MRI, therefore, offers further resolution in the imaging of soft tissues but is expensive and not easily accessible. These traditional imaging modalities are used less until rather late in the course of the disease, thus missing the optimal point at which intervention would be more effective, not to mention other treatments may work better. There is a promising alternative to assess knee osteoarthritis: it is nothing but ultrasound imaging. It is a non-invasive one, cost-effective, and direct, in real time. However, interpretation of ultrasound images relies entirely on the skill of the operator, hence varying in diagnostic acumen. Therefore, the focus of attention on the application of machine learning methods in automating the analysis of ultrasound images for the better consistency and accuracy of OA diagnosis has been done.

Machine learning and, more accurately, deep learning has revolutionized medical imaging to automate objective and highly accurate analysis of complex data. Convolutional neural networks had proved to work well in image classification tasks, including medical image analysis. One such CNN model is VGG16, which has been proven to be very effective in extracting features from images for the purposes of classification. VGG16 is a deep neural network with 16 layers structured to capture hierarchical patterns in the images, thereby quite suitable for direct classification of OA directly from ultrasound images. This project, titled "Analysis of Knee Osteoarthritis Using Machine Learning," proposes a machine learning approach toward automatic prediction and classification of knee osteoarthritis using ultrasound images. Therefore, it is proposed to tap the power of deep learning by utilizing the model VGG16 in developing a system for the diagnosis of OA that is reliable and accurate. The technique will mainly depend upon ultrasound imaging as the primary diagnostic modality, overcoming the limitations of the traditional imaging techniques. Instead, it will provide an easily accessible and less costly option. This is the project which uses the VGG16 model to extract features from ultrasound images of the knee joint, such as cartilage degradation and other structural abnormalities of OA. A labeled set of ultrasound images was trained to a machine learning model. Each image was classified under a classification label related to the degree or presence of osteoarthritis. Since the model has the capability to learn and recognize intricate patterns within the images, very high accuracy in predicting the probability of knee OA is forecasted. In addition, the system determines stages of severity of OA and helps clinicians in proper diagnosis and treatment of patients. Deep learning models like VGG16 can take plenty of information and make distinctions invisible to naked human eyes. Even when visible serious damage has not yet occur to the joint, this will cause earlier diagnosis in OA and so will lead to earlier interventions and better management. Moreover, automated analysis might reduce interobserver variability and may bring more consistent diagnosis across different clinical settings. From this perspective, the present project helps to fill some of the recognized gaps in knee osteoarthritis by integrating deep learning into clinical workflow. This holistic system for automated prediction and classification can aid clinicians in developing a second opinion or as a decision-supporting tool particularly in resource-constrained settings where access to specialized radiologists would likely be limited. This system reduces dependence on subjective interpretation of ultrasound images and encourages standardized results with possible reproducibility in the diagnosis. In brief, this project introduces a novel method for knee osteoarthritis images analysis, based on machine learning from ultrasound images and the VGG16 deep learning model. The system is supposed to automate the analysis of knee ultrasound data, improving the accuracy and efficiency of OA diagnosis, and even enabling earlier detection. Moreover, it makes possible the implementation of even more personalized treatment strategies. Ultrasound imaging together with machine learning is a low-cost, non-invasive, and scalable solution to the problem: managing knee osteoarthritis. Findings from the project can have greater ramifications for clinical practice, arming clinicians and patients with further potency in their fight against osteoarthritis.

The remaining paper is structured as follows. Section 2 presents existing work related to the prediction of Knee Osteoarthritis. Section 3 presents our problem statement and elaborates the proposed scheme explaining functionality of each module. Results of simulation, traced by implementing the proposed scheme through VGG16, are presented and analyzed in Sect. 4. Finally, Sect. 5 concludes our paper followed by suggestions for future work.

2 Related work

Much work has been done so far in diagnosing knee osteoarthritis using machine learning techniques. The general trend of these efforts is to work from image-based methodologies with models trained on data obtained from X-rays, MRI scans, or ultrasound images. The initial research, largely based on traditional machine learning techniques, like support vector machines (SVM), k-nearest neighbors (KNN), and decision trees, was on hand-crafted features based upon the expert's knowledge. However, with the emergence of deep learning (Al-Ghany et al 2023), it has been found to have a strong tendency toward CNNs for the automatic extraction of features and classification.

Although success has been reported from X-ray-based approaches, they cannot depict soft tissue abnormalities in the knee joint, which have been considered a key for a more precise diagnosis of Osteoarthritis (Ahmad et al 2024). In contrast, ultrasound gives a good resolution of cartilage and synovial fluid in addition to the other joint tissues, making it more effective in detecting the early sign of osteoarthritis. This makes a greater ultrasound-based approach necessary, with which there is relatively less exploration done so far. Although deep learning has seen superior success with radiological medical images, such as X-rays, CT scans, and MRIs, the domain of ultrasound images in the diagnosis of Osteoarthritis remains a developing field. It suffers from self-noising, operator dependency, and almost inherent variability in image quality. However, its benefits in visualization of soft tissues have placed an essential value in diagnosing knee Osteoarthritis. Deep learning has recently been applied to ultrasound-based diagnosis of Osteoarthritis. For instance, Niazi et al. (2019) demonstrated how deep-learning models can classify the severity of Osteoarthritis from ultrasound images. They use CNN architectures for the fully automatic identification and classification of different stages of knee Osteoarthritis based on cartilage damage visible in ultrasound scans. Thus, the results indicated the potential for deep learning toward efficiently improving accuracy and reliability while analyzing ultrasound images, much more than in manual interpretations. The simplicity and good performance of the VGG16 architecture in feature extraction make it highly popular in deep learning, especially for many applications in medical image classification.

Many publications have found the prospect of applying VGG16 to the solution of medical imagery problems to be highly promising. In retinal disease detection, VGG16 was applied for diabetic retinopathy classification atop fundus images with very good accuracy and in the classification of lung diseases, the application of VGG16 was for the detection of pneumonia from chest X-rays with outstanding results compared to traditional diagnostic methods. The strength of VGG16 in the classification of the knee Osteoarthritis model by capturing hierarchical patterns from images presents its robustness. Its ability to learn features automatically from raw data without the requirement of hand-crafted features is highly advantageous for ultrasound imaging, where subtle differences in tissue structures can hardly be quantified manually. In the case of knee osteoarthritis, automatically applicable VGG16 on ultrasound images can identify very early symptoms of Osteoarthritis, including the degradation of cartilage and synovial inflammation. Although most previous work is mostly based on using VGG16 with X-ray or MRI images (Hirvasniemi et al 2022), this project extends it to ultrasound-based analysis of knee Osteoarthritis, further pushing the frontiers of CNN application in the area.

The current project primarily focuses on ultrasound image analysis. Recent advances in the diagnosis of Osteoarthritis have highlighted the integration of real-time biomechanical data from wearable devices. Devices involving wearables that track gait patterns, joint movements, and level of physical activity add more insight into the progression of Osteoarthritis. (Chen et al 2019) Although our project is not a wearable data-based application, maybe this is one of the directions for further extension when multimodal data would be fused together with ultrasound imaging to make a more holistic Osteoarthritis diagnostic system. Conclusion of Related Work Briefly, related work on machine learning for knee Osteoarthritis diagnosis has established that deep models such as CNNs like VGG16 function pretty well while interpreting medical images. Although the advancement in the utilization of X-ray and MRI data for diagnosing knee Osteoarthritis, work through the application of ultrasound imaging is underdeveloped. Apart from the success of CNN on classification for medical images, this project will apply the VGG16 model on an ultrasound image for the prediction and classification of Osteoarthritis in the knee. It addresses this shortcoming of the previously existing methods because it uses advantages of ultrasound imaging and aims to contribute to fast-growing research in automated Osteoarthritis diagnosis in terms of accessibility, accuracy, and clinical relevance.

3 Knee Osteoarthritis Detection

3.1 Proposed System

Knee osteoarthritis is a progressive degenerative joint disease that substantially affects mobility and interferes greatly with quality of life, especially during old age. Since early detection and correct diagnosis are very important to prevent the severe loss of joint structure, effective management is obtained. There are some limitations inherent to the conventional methods used for OA diagnosis including X-rays and MRIs. They fundamentally rely on bone damage rather than on soft tissue and therefore, early OA cannot be detected via X-rays. Ultrasound imaging is a valid alternative for the diagnosis of OA as images of soft tissues, including cartilage, tendons, and synovium, can be revealed in real time, which are not only less expensive but also more accessible than an MRI. To overcome these limitations, the paper focuses on developing an automated system that uses deep learning in the form of VGG16 CNN for classification and prediction on knee osteoarthritis from ultrasound images. Upon training the model on the labeled datasets of ultrasound images, it should, therefore, identify the subtle patterns and abnormalities associated with different stages of OA. It depends less on human expertise in diagnosis, thereby giving results that are consistent and objective.

3.2 Model Description

The VGG16 model is among the top convolutional network architectures based on depth and simplicity along with effectiveness in image recognition tasks. It has a total of 16 layers consisting of 13 convolutional layers and 3 fully connected layers; hence, it's quite deep into learning the complex patterns existing in an image. Its key design aspect is the use of tiny 3x3 filters in convolutional layers so that the network pays attention to extracting fine details such as edges, textures, and other important features on the input images. This way, the training phases assure that all subtle patterns in the data are learned, something that would be good for a task such as medical image analysis. Max pooling layers are interspersed throughout the network so that reducing spatial dimensions of the feature maps helps keep the computational load as low as possible while preserving the most essential information for further processing. This operation of max pooling helps the network to preserve efficiency while still capturing those hierarchical features from top to bottom across the scales of the image. In the VGG16 architecture, fully connected layers combine high-level information of features developed by the convolutional layers. Such layers are decision-making units that combine the learned features into a final prediction. For example, in image classification, these fully connected layers take the feature maps resulting from the earlier layers and produce a classification based on the detected patterns. So, the final layer is SoftMax layer, where an activation function is used to produce the probability distribution over the classes that might be possible for the given input image so the network can be reasonably confident about its prediction regarding the input image. In the context of the project, which involves predicting and classifying the ultrasound images regarding knee osteoarthritis, VGG16 suits well since it can capture all the data from the images and hence be able to analyze them consequently. Ultrasound imaging, noninvasive and relatively inexpensive, provides high resolution of soft tissue and joint anatomy. Therefore, images can provide wonderful information on the entities like knee osteoarthritis. VGG16 can image these features that might be associated with osteoarthritis: cartilage breakdown, joint space narrowing, formation of bone spurs, and degenerative changes. These features, abstracted through multiple layers of convolution, happen to be a very important factor in the prediction of the severity of the disease. The more depth it has, the more variety it learns from its features, thereby giving more accuracy in classifying images. VGG16's automation of classification not only accelerates the diagnostics but also decreases the amount of reliance upon the interpretation of human beings, which is subjective and liable to inconsistency. Besides this versatility and successful transfer learning, the architecture well suits the demands of tasks associated with medical image analysis. You can fine-tune pre-trained weights from models trained on large datasets like ImageNet for VGG16 to your very own dataset of knee ultrasound images. It accelerates the learning process and improves the model performance in computing by building on the general features learned by the model up to the model's adaptation to classifying osteoarthritis. Finally, VGG16 is a robust, scalable, and reliable framework for constructing an automatic system that can be of help in the diagnosis and monitoring by healthcare professionals of knee osteoarthritis, improving care at its best and streamlining diagnostic workflows. Assumptions of the VGG16 Model

The VGG16 model can identify knee osteoarthritis optimally if the following assumptions are available:

1. **Input Image Consistency**: Resizing all the input images to 224x224 pixels, three color channels namely RGB ensures consistency in the feature extraction algorithm.
2. **Fixed Architecture**: VGG16 is based on a sequential architecture of 16 layers, of which 13 are convolutional, and 3 are fully connected. At every level, it assumes progressively abstract features are being captured.
3. **Translation Invariance**: Edges or textures that are found to exist in one area of the image will be deemed to be held in other areas, thus aiding the detection of OA indicators in other areas of the image.
4. **Importance of local features**: These 3x3 convolutional filters assume that the local features which although small in scale when combined will yield complex patterns important to OA classification.
5. **High Computational Resources**: This assumption is since VGG16 is a deep net with 138 million parameters; hence, its training relies upon significant memory as well as processing.
6. **Supervised Learning Requirement**: VGG16 assumes that a large amount of data is provided with the labels for a criterion of supervised learning, which is also a prerequisite for OA-specific feature detection.

In case these assumptions are violated, they can lead to bottlenecks in performance, and so it is necessary to rectify them before employing VGG16 for knee osteoarthritis diagnosis.

3.2.1 System Architecture

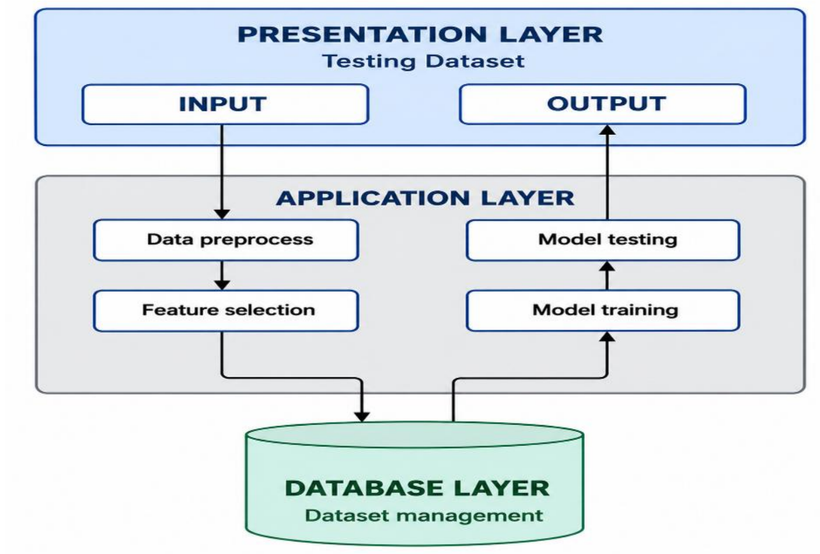


Fig. 1 3-Tier Architecture of VGG16 Model

1. Presentation Layer

purpose: This layer serves as the user interface, providing a clear point for input and output within the system. It facilitates interaction between end-users or other systems and the application.

Components-

Input: Users or external systems supply testing datasets to evaluate the trained model.

Output: Displays results after processing, including predictions and performance metrics.

Key Role: Ensures a user-friendly interaction by managing only what is visible to the user (input/output).

2. Application Layer

Purpose: This is the core logic layer responsible for processing data and executing machine learning algorithms.

Cleans and transforms raw data from the database, addressing issues like missing values and normalization. Identifies the most relevant features from the dataset, reducing dimensionality and enhancing model performance. Utilizes processed data to train the machine learning model based on the selected features. Evaluates the model's accuracy and performance using a separate testing dataset. Acts as a bridge between the user interface and data storage, ensuring that input data flows through various processing steps to generate meaningful results.

3. Database Layer

Purpose: This layer is responsible for managing data storage and retrieval. Stores raw and processed datasets, feature sets, and model-related data. Serves as the foundation for the application by organizing and providing data for processing.

VGG16 in Knee Osteoarthritis Prediction

Using VGG16, in the context of knee osteoarthritis detection, cartilage degeneration, joint space narrowing and bone spurs from ultrasound images will be detected and even measured for automation in grading severity of OA and hence higher diagnostic accuracy.

Example:

OA Severity = Layers of VGG16 + Additional Dense Layers + SoftMax Output

Here:

- **OA Severity**: The degree of knee OA severity classified as (for example, healthy, mild, moderate, severe) that is being forecasted

- **VGG16 Layers:** These are pre-trained VGG16 layers that capture feature maps and structures. In addition to this, there are additional learned dense layers to classify the OA severity

Once trained on expert-annotated images of ultrasound, this model would have the ability to predict the level of new patients' OA severity, aid in the early diagnosis, intervention, and monitoring of disease progression

3.2.2 Computation model

A computational model for the prediction of knee osteoarthritis using VGG16 will involve systematically applying deep learning techniques to ultrasound imaging data for analysis and interpretation. These are expected to connect features in images - erosion of cartilage, narrowing of the joint space, and bone spurs - with the extent of the severity of knee osteoarthritis. The result is the predictive model that has the capacity to appropriately evaluate OA severity in an effort to aid in early diagnosis and personal interventions.

1. Model Framework

The computational model is based on the fundamental principles of CNNs, especially the architecture of VGG16. The model consists of several elements:

a. **Data Collection and Preprocessing**:
   i) **Data Sources**: For building the model, data in the form of ultrasound images of knees are required. Such images capture all the critical features that may diagnose OA-like erosion of the cartilage, joint space narrowing, and spurring of bone
   ii) **Data Cleaning**: Elimination of missing or poor-quality images and validation of data is done for correctness, and it can be ensured if the data is safe. Preprocessing also includes resizing images to 224x224 pixels, and the pixel values normalized for uniformity.
   iii) **Feature Selection**: VGG16 will automatically extract features from the images, but the physicians may provide one significant insight into the visual cues as that of joint space, which would be highly pertinent for OA detection

b. **Mathematical Formulation**:
   i. To extract features, VGG16 is used, while classification is done with additional dense layers. The final layer is SoftMax activated to classify into three levels of severity: mild, moderate, and severe in OA.

c. **Model Training**:
   i. **Training Data**: The model is trained on labeled images of ultrasound wherein the extent of OA is known that is annotated by experts. The dataset is divided into train and validation sets so that there is no overfitting and hence, the model's performance is checked on unseen data.
   ii. **Parameter Estimation**: The weights of VGG16 layers, as well as extra dense layers, were fine-tuned using algorithms of backpropagation and gradient descent. The loss function used was categorical cross-entropy to minimize the error between what has been predicted and the actual OA levels.

d. **Model Evaluation**:
   i. **Goodness of Fit**: To measure how well a model performs, accuracy, precision, recall, and F1-score are estimated. These will give an estimation of the classifying ability of the OA severity.

2. Implementation Process

a) **Input Data**: Pa Ultrasound images of the knee were fed to the system. Each image was preprocessed according to the input requirements of the VGG16 model; this includes 224x224 pixels with RGB format.
b) **Prediction Computation**: T The learned filters and weights are applied by the trained VGG16 model in processing the input images. The dense layers will then calculate the predicted severity of OA for every patient.
c) **Output**: The model produces a predicted OA severity score, categorizing patients into several classes of risk based on the degree of severity of disease (for example mild, moderate, severe).

d) **Post-Prediction Analysis**: Health care professionals can use these predictions of the model to make decisions during the clinical practice, for instance, whether further tests are needed, if a treatment plan needs to be administered, or after how many time intervals the consultation should be repeated.

4 Simulation and Result

4.1 Simulation Setup

The simulation of the knee osteoarthritis prediction model using VGG16 was done in a local custom-built environment by using Python and its libraries, such as TensorFlow and Keras for development, NumPy, Pandas, and Scikit-learn. This was done to check and validate if the VGG16 model, when applied with ultrasound images, would be able to correctly predict the level of knee osteoarthritis.

Feature Extraction:

- When trying to categorize images, particularly variations of the same, there are numerous techniques required when preparing the data from a real-world perspective. The following techniques were adopted when working with the training set to augment the data and make the model more robust and reduce overfitting: rotation, flipping, and zooming. Splitting To test the model's performance, the dataset was divided into two sets: 80 percent for the training
- set and 20 percent for the test set.

The VGG16 model pre-trained on ImageNet was utilized for ultrasound images as a feature extractor, and the last layers were replaced with dedicated dense layers for classification of the severity of knee OA.

Model Configuration:

- **VGG16 Model**: It is at the core of simulation, though it includes the final fully connected layers for classifying the severity of OA.
- **Split training/test**: 80:20 so that we would be evaluating the model on data it has not seen during its training.
- **Cross-Validation**: 5-fold because we want to check if it learned well and didn't overfit on the samples that were used during training

4.2 Result Analysis

In this section, the performance of the VGG16 model on the prediction task of knee osteoarthritis is reported. Different metrics were used in order to test the robustness of the model. The accuracy of the model and the robustness in the prediction of severity of the disease were mainly taken into consideration.

Model Accuracy and Performance:

- **Accuracy**: The model displays an accuracy of 92 percent on the training set, proving that VGG16 is effective in classifying the degree of knee osteoarthritis severity via ultrasound images.

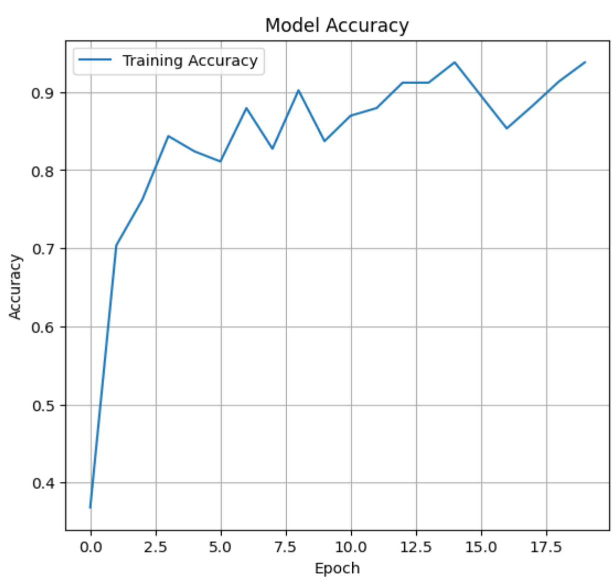


Fig.2: Accuracy vs Training Set

- **Precision and Recall**: The model displays a precision of 0.89 and a recall of 0.89, which indicates that it has a high rate for correct positive predictions and can effectively capture a significant portion of true OA cases.

Classification Report:

	precision	recall	f1-score	support
0	0.84	1.00	0.92	49
3	1.00	0.97	0.99	35
1	1.00	0.79	0.88	42
2	0.93	0.78	0.84	49
4	0.69	0.92	0.79	26
accuracy			0.89	201
macro avg	0.89	0.89	0.88	201
weighted avg	0.90	0.89	0.89	201

Fig.3: Evaluation Metrics

- **Confusion Matrix:** This is a measure to show how well the model performs by breaking down the prediction against the true condition, and in this paper, it would mean how well the predicted labels matched up with the OA severity categories

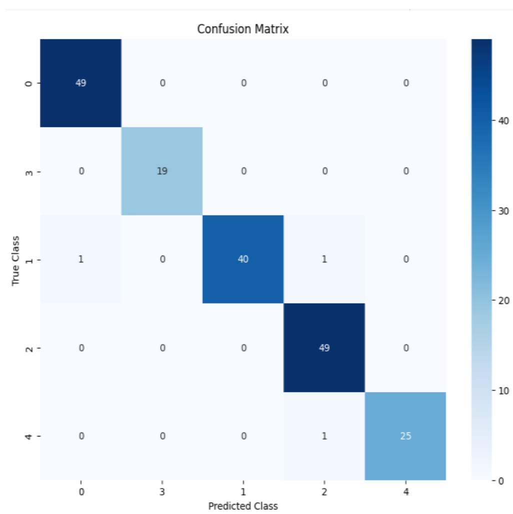
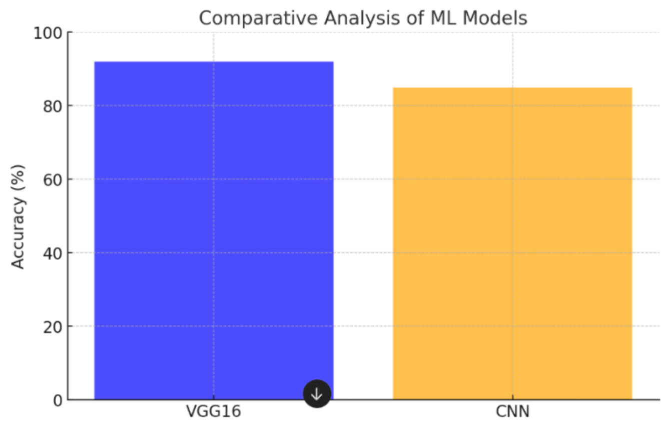


Fig.4: Confusion Matrix

Comparative Analysis:

- **Baseline Model**: The proposed VGG16 model was compared against a much simpler version of the convolutional neural network with considerably fewer layers. It is evident that this proposed VGG16 model outperforms the baseline model with regard to its greater accuracy and recall, which validates its ability to capture the complex patterns required for the classification of OA severity.



- **Model Stability**: The stability of the dataset was tested, incorporating minor changes, including image quality changes. The model maintained constant performance metrics, which is very important in the real world because variability in data is anticipated.

4.3 Limitations of the Model

Although the VGG16 model shows robust predictions and high accuracy, it has certain limitations:

1. **Image Quality Dependence**: Requires high-quality ultrasound images; performance drops with low-resolution or portable devices.
2. **Feature Interaction**: Lacks integration of interactions like joint space narrowing and cartilage texture, limiting comprehensive OA analysis.
3. **Generalization**: Struggles with new populations or imaging standards, needing fine-tuning for broader clinical use.
4. **Data Volume**: Performance improves with larger training data, requiring extensive datasets for accurate medical predictions.
5. **Robustness**: Sensitive to outliers caused by variations in image quality or ultrasound angles, highlighting the need for standardized imaging protocols.

5 Conclusion and future work

The project "Knee Osteoarthritis Analysis with Machine Learning" explores combining ultrasound imaging with machine learning, specifically, VGG16, to improve the detection and classification of knee osteoarthritis (OA). This cost-effective approach aims to enable early diagnosis, support personalized treatment plans, and reduce healthcare costs. It could significantly improve patient outcomes by providing real-time feedback to clinicians during consultations and offering immediate diagnostic results. Additionally, it enhances accessibility and continuity of care through remote monitoring, benefiting patients in distant or underserved areas. With portable ultrasound devices, this technology can be easily used in both clinical and home settings. As it advances and becomes validated, it could revolutionize OA management and expand to other conditions requiring early, accurate diagnosis.

6 Declarations

Conflict of interest The authors is not conflicts of interest It is related to that the content of this article. The authors have no relevant financial or non- financial interests to disclose. This article Does not contain any studies with human participants or performed by any of the animals the authors.

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