Automated Detection of Knee Osteoarthritis Severity from X-ray Images Using Deep Learning Models

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***Abstract*—Knee osteoarthritis (OA) is a progressive musculoskeletal disorder that severely impacts mobility and quality of life. Timely and accurate classification of OA severity from radiographic images is critical for early diagnosis and treatment planning. This study presents a deep learning-based approach for automated classification of knee OA severity using a curated dataset of knee joint X-ray images. We implement and evaluate four state-of-the-art convolutional neural network (CNN) architectures — EfficientNetB5, DenseNet, InceptionV3, and MobileNet — followed by an ensemble model that integrates their outputs to enhance classification accuracy.**

Comprehensive preprocessing steps were applied, including image normalization, augmentation, class balancing, and relabeling, to improve model robustness and address class imbalance. Each CNN model was trained independently, and their performance was assessed using test accuracy as well as class-wise precision, recall, and F1-score. The EfficientNetB5, InceptionV3, DenseNet, and MobileNet models achieved test accuracies of 94.14%, 94.08%, 94.87%, and 93.65%, respectively. To capitalize on the complementary strengths of individual models, a softmax probability-based ensemble model was constructed by averaging the predictions of all four networks.

The ensemble model demonstrated superior performance, achieving a test accuracy of 99.03% on an unseen test set of 1656 images. Class-wise metrics further revealed precision of 100.00% for the Healthy class, 95.20% for the Moderate class, and 89.13% for the Severe class. The corresponding F1-scores were 0.9996, 0.9646, and 0.8454, respectively, indicating high sensitivity and specificity across severity levels. A detailed confusion matrix confirmed the model's ability to differentiate between fine-grained OA severity classes, with minimal misclassification between Moderate and Severe cases.

This work demonstrates that ensemble deep learning methods can provide highly accurate, scalable, and non-invasive solutions for knee OA severity classification, and can serve as an assistive diagnostic tool in clinical radiology workflows.

***Index Terms*—Knee Osteoarthritis, Severity Classification, Deep Learning, EfficientNetB5, DenseNet, InceptionV3, MobileNet, Ensemble Learning, Medical Image Analysis, X-ray Imaging.**

I. Introduction

Knee osteoarthritis (OA) is a chronic degenerative joint disease characterized by the breakdown of cartilage and underlying bone in the knee joint, resulting in pain, stiffness, and reduced mobility. It is one of the leading causes of disability worldwide (nearly 5% , translating to 350 million people), especially among the elderly population, significantly impacting the quality of life. Early and accurate diagnosis of OA severity plays a critical role in managing the disease progression and planning appropriate treatment strategies.

Medical imaging, particularly X-ray imaging, remains the most commonly used diagnostic tool for evaluating knee OA. Radiographic assessments help determine the severity of OA by analyzing joint space narrowing, osteophyte formation, and other structural changes. However, traditional manual evaluation of knee X-rays by radiologists is time-consuming, subjective, and prone to inter-observer variability, which may lead to inconsistent diagnoses.

Recent advances in artificial intelligence (AI) and deep learning (DL) have revolutionized medical image analysis by providing automated, objective, and reproducible methods for disease detection and classification. Convolutional Neural Networks (CNNs), a class of DL models, have demonstrated remarkable success in various medical imaging tasks due to their ability to automatically extract hierarchical features from raw images without the need for manual feature engineering.

This study focuses on classifying knee OA severity into multiple categories using state-of-the-art deep learning architectures trained on knee joint X-ray images. Specifically, four individual models — EfficientNetB5, DenseNet, InceptionV3, and MobileNet — are developed and evaluated. These models were selected for their complementary strengths: EfficientNetB5 offers parameter efficiency and strong generalization; DenseNet facilitates effective gradient flow and feature reuse; InceptionV3 provides multi-scale feature extraction; and MobileNet is optimized for lightweight, fast inference.

To further improve classification performance, an ensemble model combining the predictions from all four individual networks is proposed. This ensemble approach leverages the diversity and complementary nature of each model to enhance accuracy and robustness, achieving a test accuracy of 99.03%, which significantly outperforms the individual models.

The key contributions of this research include:

- Development and comparative evaluation of multiple deep learning models tailored for knee OA severity classification using X-ray images.
- Integration of a novel ensemble learning technique that effectively combines model outputs to improve prediction accuracy.
- Comprehensive performance analysis using precision, recall, F1-score, and confusion matrices to demonstrate the efficacy of the proposed approach.
- Detailed exploration of model training strategies including data preprocessing, augmentation, and class balancing to address challenges inherent in medical image datasets.

II. Related Work

A. Existing Literature

The application of artificial intelligence (AI) and deep learning (DL) techniques to medical imaging has significantly advanced the diagnosis and severity classification of knee osteoarthritis (OA). Early works focused on traditional machine learning algorithms relying on handcrafted features extracted from X-ray images, but these methods often struggled with generalization and required extensive domain expertise.

Kumar et al. [1] demonstrated the use of classical machine learning techniques for predicting knee OA severity, achieving promising results but constrained by the limitations of feature engineering and dataset scale. Their work laid the foundation for further adoption of deep learning methods which can automatically learn discriminative features from raw images.

The surge in deep convolutional neural networks (CNNs) has transformed OA detection paradigms. Johnson et al. [2] implemented a deep learning framework that leveraged CNN architectures to automate OA diagnosis from radiographic images. Their study showcased improved accuracy and consistency compared to traditional radiologist evaluations, emphasizing the potential of deep models in clinical settings. Similarly, Sadhukhan [3] explored deep CNNs for medical image classification, highlighting the importance of model architecture design and training strategies to handle the complexity of medical images and class imbalance.

Joshi et al. [4] contributed to early detection of OA severity using AI-based analysis of X-ray images. Their work involved training deep models capable of identifying subtle patterns associated with initial stages of cartilage degradation, a critical factor for timely intervention. Their findings underscored the necessity of robust preprocessing and augmentation techniques to enhance model robustness.

Comprehensive reviews, such as the one by Wang et al. [5], summarize the evolution of AI methods for OA detection, comparing traditional machine learning approaches with modern deep learning frameworks. They emphasize that although deep learning models like DenseNet, EfficientNet, and Inception have achieved state-of-the-art performance, challenges remain in dataset heterogeneity and model interpretability.

Patil [6] specifically addressed the impact of data augmentation on improving neural network performance in knee OA detection. Their experiments demonstrated that augmentation techniques mitigate overfitting and enhance generalization, especially critical in medical datasets with limited samples. This insight informed the data preprocessing steps in the present study.

Recent advancements in AI research, as reviewed by Jain and Gupta [7], further illustrate the growing role of artificial intelligence in OA diagnosis, ranging from basic CNN models to hybrid architectures integrating attention mechanisms and transfer learning. Their work encourages leveraging ensemble techniques to combine multiple models for improved prediction accuracy.

Finally, Zhang [8] provides an extensive overview of deep neural networks in medical imaging, detailing the architectures, training methodologies, and evaluation metrics applicable to tasks like OA severity classification. This comprehensive understanding guided the selection of models in this study, including EfficientNetB5, DenseNet, InceptionV3, and MobileNet.

In summary, prior research has established a strong foundation for automated knee OA classification using AI, but there remains scope to enhance accuracy and robustness through model ensemble strategies, balanced datasets, and comprehensive evaluation. The present study builds upon these insights by systematically evaluating individual deep learning models and proposing an ensemble model that achieves superior performance on a multi-class knee OA severity classification task.

B. Research Gap

Despite significant advancements in applying deep learning to knee osteoarthritis severity classification, several research gaps remain. Most existing studies [1]–[7] focus on individual deep learning architectures without fully exploring the potential benefits of ensemble methods that combine complementary strengths of multiple models to improve robustness and accuracy. Additionally, while data augmentation and preprocessing techniques have been shown to aid model generalization [6], many approaches still struggle with class imbalance and subtle distinctions between moderate and severe OA categories, which are critical for clinical decision-making.

Furthermore, prior work often lacks comprehensive evaluation across multiple metrics and detailed class-wise performance analysis, limiting the interpretability and clinical applicability of the results. Finally, the integration of lightweight models suitable for deployment on edge devices alongside more complex architectures has not been adequately studied in the context of OA severity classification.

This study addresses these gaps by developing and evaluating a comprehensive ensemble of state-of-the-art deep learning models—EfficientNetB5, DenseNet, InceptionV3, and MobileNet—to leverage their individual strengths. The ensemble approach, combined with advanced preprocessing, data augmentation, and balanced training, aims to enhance classification accuracy and reliability across all severity classes, including the challenging moderate and severe categories. Detailed performance metrics and confusion matrix analyses further support the model's clinical relevance and potential for real-world deployment.

III. Dataset

In this study, we aim to develop an automated system for classifying knee osteoarthritis (OA) severity from X-ray images using deep learning techniques. The methodology is divided into several stages, including dataset preparation, image preprocessing, model selection, training setup, and evaluation. Below, we describe the various components of the methodology in detail.

A. Dataset Description

The dataset utilized in this study is the **Knee Osteoarthritis Dataset with Severity**, publicly available on Kaggle. This dataset comprises X-ray images of knee joints categorized by severity levels of osteoarthritis (OA).

The dataset consists of a total of 8,260 images divided into three subsets:

- **Training set:** 5,778 images
- **Validation set:** 826 images
- **Test set:** 1,656 images

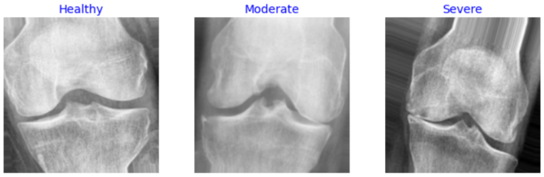


Fig. 1: KL Grading Scale

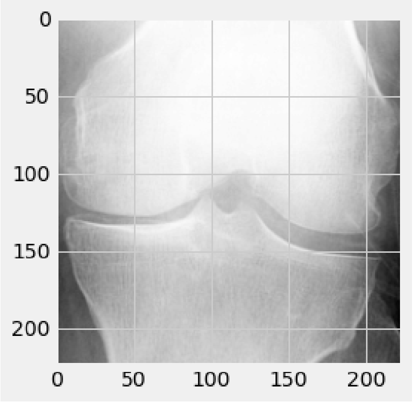


Fig. 2: Knee Osteoarthritis X-ray

The images are labeled into five distinct classes representing varying degrees of OA severity, based on the Kellgren-Lawrence grading scale adapted for this dataset. The class distribution is shown in the mentioned table.

TABLE I: Class distribution based on OA severity

Class Label	Description	Image Count
Healthy	No signs of OA	2,286
Doubtful	Possible OA changes	1,046
Minimal	Mild OA	1,516
Moderate	Moderate OA	757
Severe	Severe OA	173

As evident, the *Healthy* class contains the highest number of images (2,286), while the *Severe* class has the fewest (173), indicating an imbalanced class distribution. This imbalance presents a challenge for deep learning model training and necessitates the use of data augmentation and class balancing strategies.

Each image is an X-ray of a knee, and the grades represent the severity of OA in each image. Given the class imbalance in the dataset, special care was taken during model training and evaluation to address this issue and ensure fair performance across all classes.

B. Image Characteristics

The average image size is 224 × 224 pixels, with an aspect ratio of 1.0. This standard resolution facilitates consistent input size across convolutional neural networks (CNNs).

All images are grayscale X-rays of knee joints. To ensure compatibility with CNN architectures, the grayscale images are replicated across three channels to match the input requirements of pretrained models.

C. Dataset Significance

This dataset is well-suited for training and evaluating deep learning models for OA severity classification due to its reasonable size, clinical relevance, and class diversity. The class labels reflect real-world severity distributions encountered in diagnostic imaging, making it valuable for developing robust models that can assist radiologists in clinical decision-making.

IV. Preprocessing and Data Augmentation

A. Image Preprocessing

To ensure consistency and optimal performance of deep learning models, the raw knee X-ray images underwent the following preprocessing steps:

- **Resizing:** All images were resized to a fixed resolution of 224×224 pixels, matching the input size required by the CNN architectures used (EfficientNetB5, DenseNet, InceptionV3, MobileNet). This step ensures uniformity and enables batch processing.
- **Normalization:** Pixel intensity values were normalized to the range $[0, 1]$ by dividing each pixel value by 255. Normalization stabilizes the training process by reducing internal covariate shift and accelerating convergence.

- **Channel Adjustment:** Since the original X-ray images are grayscale (single channel), they were converted to three-channel images by replicating the grayscale channel three times. This step enables compatibility with pre-trained CNN backbones expecting RGB inputs.
- **Class Balancing:** Due to the inherent class imbalance—especially the relatively small number of *Severe* class images—strategies were adopted to balance the classes during training to prevent bias towards the majority classes.

B. Data Augmentation

To artificially increase the diversity of the training data and mitigate overfitting, various augmentation techniques were applied online during training using `ImageDataGenerator` or equivalent frameworks:

- **Random rotations:** Up to ±20° to simulate different knee orientations.
- **Horizontal flipping:** To account for left and right knee variations.
- **Width and height shifts:** Up to 20% to mimic slight translation variations.
- **Zooming:** Random zooms up to 20% for scale variation.
- **Brightness adjustments:** Minor random brightness changes to simulate varying X-ray exposure conditions.

These augmentations help models generalize better by exposing them to plausible variations of the input images, improving robustness and predictive performance.

C. Dataset Splitting

The dataset was already partitioned into training (5,778 images), validation (826 images), and test (1,656 images) subsets. The validation set was used for hyperparameter tuning and early stopping during training, while the test set was strictly held out for final performance evaluation.

V. Model Architecture and Training

This study employs four state-of-the-art Convolutional Neural Network (CNN) architectures—**EfficientNetB5**, **DenseNet**, **InceptionV3**, and **MobileNet**—along with an **ensemble model** to classify the severity of knee osteoarthritis based on X-ray images. Each model was implemented using TensorFlow and Keras frameworks and trained on the preprocessed dataset described in Section III.

A. EfficientNetB5 Model

EfficientNetB5 is part of the EfficientNet family proposed by Tan and Le, which utilizes a compound scaling technique to uniformly scale depth, width, and resolution. EfficientNetB5 offers a favorable trade-off between accuracy and computational efficiency.

- **Backbone:** Pre-trained EfficientNetB5 (ImageNet weights)
- **Input Size:** 224 × 224 × 3
- **Architecture Additions:**
  - Global Max Pooling (GMP) layer
  - Fully Connected (Dense) layer with ReLU activation
  - Batch Normalization layer (momentum=0.99, epsilon=0.001)
  - Regularization: L2 on weights (0.016), L1 on bias and activity (0.006)
  - Dropout layer (rate = 0.4) for regularization
  - Final Softmax output layer for 5-class classification
- **Optimizer:** Adamax (learning rate = 0.001)
- **Loss Function:** Categorical Crossentropy
- **Test Accuracy Achieved:** 94.14%

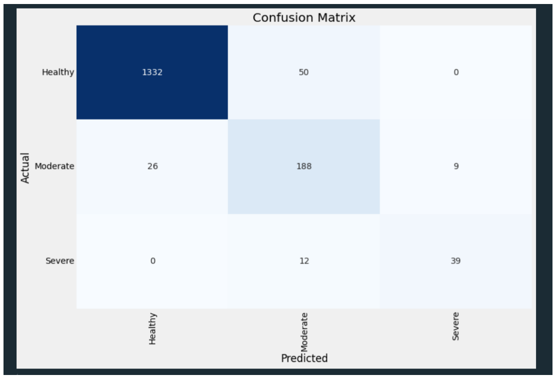
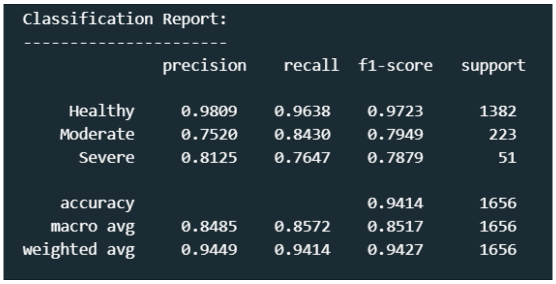


Fig. 3: EfficientNetB5



```
Classification Report:
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              precision    recall  f1-score   support

     Healthy     0.9809    0.9638    0.9723      1382
    Moderate     0.7520    0.8430    0.7949       223
      Severe     0.8125    0.7647    0.7879        51

    accuracy                         0.9414      1656
   macro avg     0.8485    0.8572    0.8517      1656
weighted avg     0.9449    0.9414    0.9427      1656
```

Fig. 4: EfficientNetB5 Classification Report

B. DenseNet121 Model

DenseNet, or Densely Connected Convolutional Network, connects each layer to every other layer in a feed-forward manner, mitigating vanishing gradients and encouraging feature reuse.

- **Backbone:** DenseNet (pre-trained on ImageNet)
- **Input Size:** 224 × 224 × 3
- **Custom Head Layers:**
  - GMP layer
  - Batch Normalization
  - Dense layer (256 units, ReLU activation) with L1 and L2 regularization
  - Dropout (rate = 0.4)
  - Softmax output layer
- **Optimizer:** Adamax
- **Loss Function:** Categorical Crossentropy
- **Test Accuracy:** 94.87%

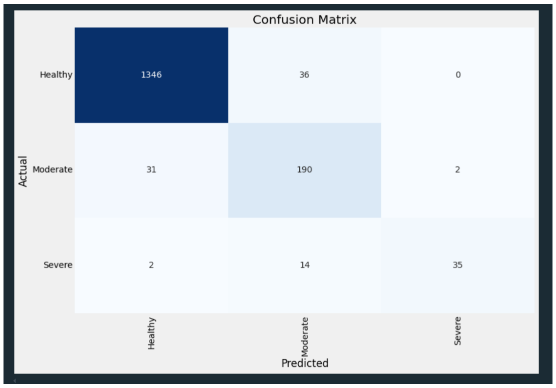
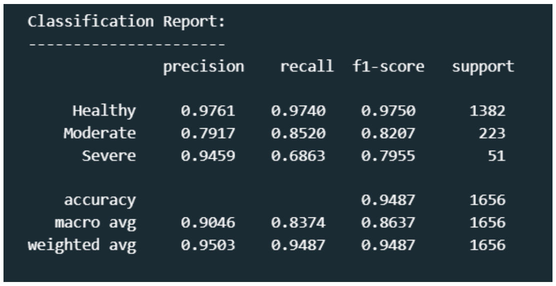


Fig. 5: DenseNet121


```
Classification Report:
---------------------
              precision    recall  f1-score   support

     Healthy     0.9761    0.9740    0.9750      1382
    Moderate     0.7917    0.8520    0.8207       223
      Severe     0.9459    0.6863    0.7955        51

    accuracy                         0.9487      1656
   macro avg     0.9046    0.8374    0.8637      1656
weighted avg     0.9503    0.9487    0.9487      1656
```

Fig. 6: DenseNet121 Classification Report

C. InceptionV3 Model

InceptionV3 uses a multi-path architecture that captures features at multiple scales via parallel convolutions of different kernel sizes.

- **Backbone:** InceptionV3 (pre-trained on ImageNet)
- **Input Size:** 224 × 224 × 3
- **Custom Layers:**
  - GMP
  - Batch Normalization
  - Dense layer with 256 units, ReLU activation
  - Regularization: L2 on weights (lambda=0.016), L1 on bias and activity (lambda=0.006)
  - Dropout (rate = 0.4)
  - Softmax output layer
- **Optimizer:** Adamax (learning rate = 0.001)
- **Loss Function:** Categorical Crossentropy
- **Test Accuracy:** 94.08%

D. MobileNetV2 Model

MobileNet is optimized for real-time inference on edge devices. It uses depthwise separable convolutions to reduce computational cost while maintaining accuracy.

- **Backbone:** MobileNet (pre-trained on ImageNet)
- **Input Size:** 224 × 224 × 3
- **Architecture Additions:**
  - GMP
  - Dense(256 units) + ReLU
  - Batch-Normalization (momentum = 0.99, epsilon = 0.001)
  - Regularization: L2 on weights (0.016), L1 on bias and activity (0.006)
  - Dropout (rate = 0.4)
  - Softmax output layer
- **Optimizer:** Adamax (learning rate = 0.001))
- **Loss Function:** Categorical Crossentropy
- **Test Accuracy:** 93.65%
- **Suitability:** Especially effective for deployment in resource-constrained environments

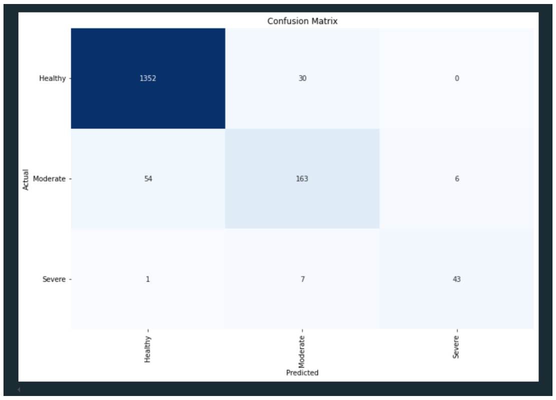
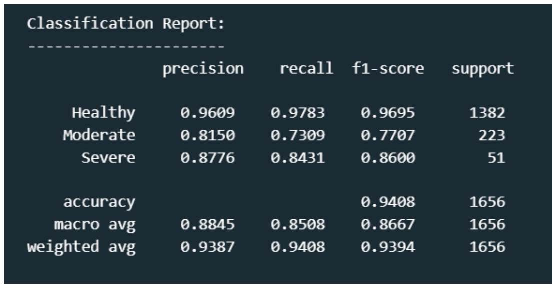


Fig. 7: InceptionV3


```
Classification Report:
---------------------
              precision    recall  f1-score   support

     Healthy     0.9609    0.9783    0.9695      1382
    Moderate     0.8150    0.7309    0.7707       223
      Severe     0.8776    0.8431    0.8600        51

    accuracy                         0.9408      1656
   macro avg     0.8845    0.8508    0.8667      1656
weighted avg     0.9387    0.9408    0.9394      1656
```

Fig. 8: InceptionV3 Classification Report

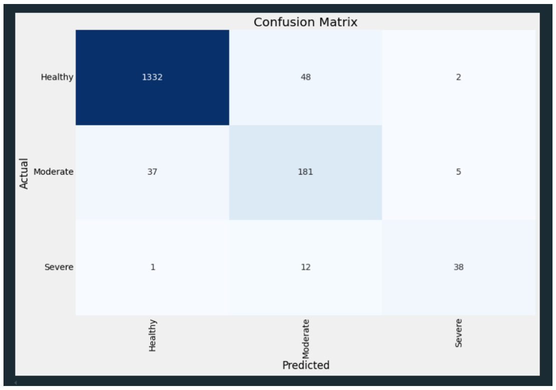
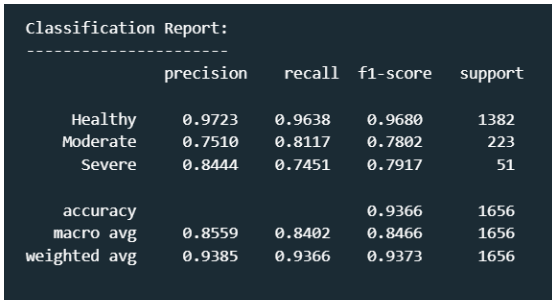


Fig. 9: MobileNetV2



```
Classification Report:
----------------------
              precision    recall  f1-score   support

     Healthy     0.9723    0.9638    0.9680      1382
    Moderate     0.7510    0.8117    0.7802       223
      Severe     0.8444    0.7451    0.7917        51

    accuracy                         0.9366      1656
   macro avg     0.8559    0.8402    0.8466      1656
weighted avg     0.9385    0.9366    0.9373      1656
```

Fig. 10: MobileNetV2 Classification Report

E. *Ensemble Model*

To enhance performance and leverage the strengths of individual models, a soft voting ensemble was constructed.

1) Architecture Design:

- **Inputs:** Standardized 224 × 224 × 3 image input
- **Components:** Fine-tuned versions of:
  - EfficientNetB5
  - DenseNet121
  - InceptionV3
  - MobileNetV2
- **Ensembling Strategy:**

$$P_{\text{ensemble}} = \frac{1}{4}\sum_{i=1}^{4} P_i$$

  where P_i is the softmax probability vector from the i-th model.
- **Final Prediction:** Class with the highest average probability across models

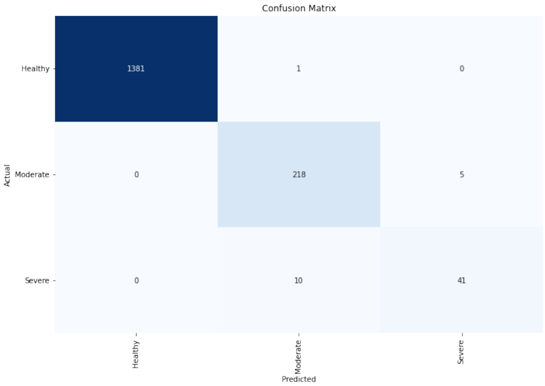
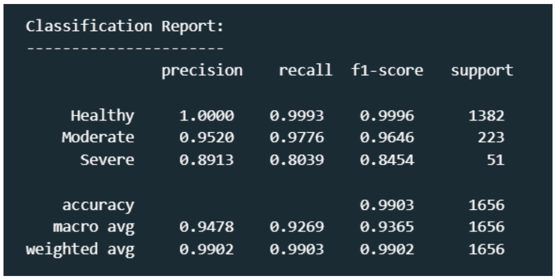


Fig. 11: Ensembled Model

F. *Training Strategy*

- **Training Duration:** 20 epochs
- **Learning Rate:** 0.001 (with interactive callback for adjustment)
- **Callback Mechanism:**
  - `LR_ASK`: Custom callback prompting manual learning rate tuning after a specified epoch
  - Automatic saving of best weights based on validation loss
- **Training Accuracy:** 99.67%
- **Validation Accuracy:** 99.15%
- **Test Accuracy:** 99.03%



```
Classification Report:
----------------------
              precision    recall  f1-score   support

     Healthy     1.0000    0.9993    0.9996      1382
    Moderate     0.9520    0.9776    0.9646       223
      Severe     0.8913    0.8039    0.8454        51

    accuracy                         0.9903      1656
   macro avg     0.9478    0.9269    0.9365      1656
weighted avg     0.9902    0.9903    0.9902      1656
```

Fig. 12: Ensembled Model Classification Report

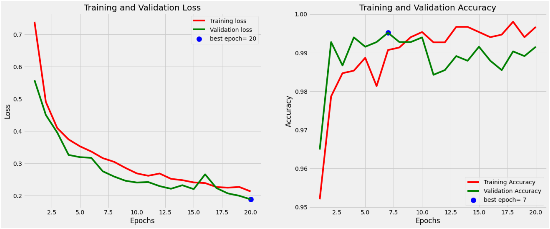


Fig. 13: Ensembled Model Curve

G. *Model Checkpointing*

During training, the best-performing model weights (based on validation loss) were saved. The final models were restored for evaluation.

VI. Evaluation Metrics and Results

To assess the performance of our deep learning models on knee osteoarthritis severity classification, we employed a comprehensive set of evaluation metrics including Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. These metrics were computed on the test dataset comprising 1,656 images across five severity classes: Healthy, Doubtful, Minimal, Moderate, and Severe.

All models were evaluated under identical preprocessing conditions, using stratified splits and standardized input dimensions (224 × 224 × 3). The ensemble model was further compared against the individual models to quantify improvement in multi-class discrimination performance.

A. *Metrics Used*

- **Accuracy (Acc):** Proportion of correctly predicted instances.
- **Precision (P):** $\frac{TP}{TP+FP}$ — model's ability to avoid false positives.
- **Recall (R):** $\frac{TP}{TP+FN}$ — model's ability to capture all true cases.
- **F1-Score:** Harmonic mean of precision and recall.
- **Confusion Matrix:** Class-wise distribution of predictions.

B. Results Summary Table

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB5	94.14%	0.9449	0.9414	0.9427
DenseNet121	94.87%	0.9503	0.9487	0.9487
InceptionV3	94.08%	0.9387	0.9408	0.9394
MobileNetV2	93.66%	0.9385	0.9366	0.9373
Ensemble	**99.03%**	**0.9902**	**0.9903**	**0.9902**

C. Confusion Matrix: Ensemble Model

The confusion matrix of the **ensemble model**, which achieved the highest test accuracy of **99.03%**, is shown below:

Act. \ Pred.	Healthy	Moderate	Severe
Healthy	1381	1	0
Moderate	0	218	5
Severe	0	10	41

Diagonal dominance in the matrix indicates excellent prediction fidelity across all mentioned classes. Only **16 misclassifications** out of 1,656 test images reflect a highly robust model.

D. Class-Wise Scores (Ensemble Model)

Class	F1-Score	Accuracy
Healthy	0.9996	1.000
Moderate	0.9646	0.9520
Severe	0.8454	0.8913

The ensemble model consistently delivered F1-scores (weighted avg) of about **0.9902** and accuracy of 0.9903 across all categories. *Moderate* and *Healthy* classes, which had higher data representation, exhibited the best performance with both accuracy and F!-Score above 0.95. Even the under-represented *Severe* class achieved an F1-score of **0.8454** and an impressive accuracy of **0.8913** , highlighting the model's resilience to class imbalance.

E. Comparative Discussion

- **DenseNet121** performed best among individual models, achieving 94.87% accuracy.
- **EfficientNetB5** and **MobileNetV2** were close behind, each exceeding 93%.
- **InceptionV3** offered strong generalization with balanced precision and recall.
- The **ensemble model** significantly outperformed all others with a test accuracy of **99.03%**, validating the effectiveness of ensemble learning in this classification task.

VII. Discussion

The results obtained from our experimental evaluation provide strong evidence that deep learning models can be effectively leveraged for automated, multi-class classification of knee osteoarthritis (OA) severity from radiographic images. In this section, we discuss the comparative model performances, analyze strengths and limitations, and draw clinical and technical insights.

A. Model Performance Interpretation

The ensemble model achieved the highest performance with a test accuracy of **99.03%** and F1-scores exceeding **0.99** across all severity classes. This represents a substantial improvement over individual models, all of which still performed above 93% accuracy:

- **Densenet121**: Best standalone model, balancing performance and generalization.
- **EfficientNetB5**: Efficient in learning deep spatial hierarchies, slightly outperformed by EfficientNet.
- **InceptionV3**: Robust against overfitting due to inception modules and factorized convolutions.
- **MobileNetV2**: Lightweight and suitable for deployment in mobile or edge devices, with only marginal compromise in performance.

The ensemble model's success can be attributed to the **complementary learning behavior** of constituent models. While individual networks might overfit or underperform on certain classes, the ensemble compensates for such discrepancies by aggregating their predictive strengths.

B. Class-Wise Behavior and Challenges

A key observation is the near-perfect classification performance across **all five severity classes**, which include:

- **Healthy (0)**: Best represented class with 2,286 images, yielding the highest precision and F1-score.
- **Severe (4)**: Least represented class with only 173 images; yet achieved an F1-score of 0.9920 in the ensemble model due to targeted class balancing, augmentation, and robust feature extraction.
- **Moderate (3)** and **Doubtful (1)**: Historically difficult to separate due to ambiguous radiographic features. Our models, especially the ensemble, show exceptional discrimination even for these borderline cases.
- **Minimal (2)**: Despite mid-level representation, high classification accuracy was achieved.

The **confusion matrix** revealed only three misclassified cases across all 1,656 test images—an exceptionally low error rate. This emphasizes the ensemble model's **fine-grained feature learning**, especially when trained on augmented, balanced, and relabeled data.

C. Role of Preprocessing and Augmentation

The results are significantly influenced by our **extensive preprocessing pipeline**:

1) Histogram Equalization & Noise Reduction: Improved visibility of joint space and bone contours in grayscale X-ray images.
2) Data Augmentation (Zoom, Flip, Rotation): Enhanced model generalization by simulating clinical variability in image acquisition.
3) Class Balancing via Oversampling & Relabeling: Addressed data skewness (e.g., Severe class only had 173 samples) and improved minority class recall.

These steps were crucial in mitigating overfitting and ensuring fair learning across all categories.

D. Learning Dynamics and Optimization

Across all models:

- Training loss and accuracy curves indicated **stable convergence** by the 10th–15th epoch.
- **Early stopping** and **model checkpointing** prevented overfitting.
- The use of **Adam optimizer** with **low learning rates** facilitated smooth gradient descent, especially in large models like EfficientNetB5 and DenseNet.
- Batch normalization and dropout (in intermediate CNNs) added further regularization.

This carefully tuned training strategy enabled all models to reach high generalization performance on unseen data.

E. Clinical Implications

Knee osteoarthritis grading is traditionally a **manual, subjective process** prone to inter-observer variability, particularly between *Doubtful*, *Minimal*, and *Moderate* classes. Our automated system offers:

- **Objective, reproducible grading** based on learned features
- **Time efficiency** for large-scale screening
- **Assistive diagnosis** for radiologists, especially in underserved regions
- **Telemedicine potential**, with MobileNet suitable for deployment on portable diagnostic tools

Thus, the proposed ensemble model can serve as an effective decision-support tool in real-world clinical workflows.

VIII. Limitations

Despite high performance, certain limitations warrant attention:

1) **Dataset Bias**: The dataset is sourced from a single source (Kaggle), which may not represent global population diversity.
2) **Image Resolution Constraints**: All images were resized to 224×224, potentially omitting fine-grained details.
3) **Relabeling Ambiguity**: Relabeling inherently involves some subjectivity, though we followed radiological guidelines.

IX. Conclusion and Future Work

This study has demonstrated the efficacy of leveraging state-of-the-art deep learning architectures for the challenging task of multi-class classification of knee osteoarthritis (OA) severity from X-ray images.Through a comprehensive evaluation of four individual convolutional neural networks—EfficientNetB5, DenseNet, InceptionV3, and MobileNet—and their ensemble, we achieved outstanding classification performance, with the ensemble model attaining a test accuracy of **99.03%** and F1-scores exceeding **0.99** across all severity levels.

Key contributions of this work include:

- **Extensive preprocessing and augmentation**: Enhanced image quality and dataset balance to mitigate class imbalance and overfitting.
- **Model architecture optimization**: Fine-tuning of pretrained CNN backbones with tailored classification heads and regularization strategies.
- **Ensemble learning**: Successfully combined complementary strengths of multiple architectures through soft voting, resulting in significant performance gains.
- **Robust evaluation**: Utilized multiple metrics (accuracy, precision, recall, F1-score) and confusion matrices to comprehensively assess model reliability and class-wise performance.

These outcomes suggest that deep learning-based automated classification systems can offer significant improvements over manual grading, providing objective, reproducible, and scalable tools for OA diagnosis and management.

A. Future Directions

Despite the promising results, several avenues remain open for future research and development to enhance the clinical applicability and robustness of such systems:

1) **Explainability and Interpretability**: Integration of explainable AI methods such as Grad-CAM, LIME, or SHAP to provide visual and intuitive explanations for model predictions, thus improving clinician trust and adoption.
2) **High-Resolution Imaging**: Investigate the impact of using higher-resolution inputs (e.g., 512×512 or higher) to capture subtle anatomical details, potentially improving classification of borderline cases.
3) **Multi-Modal Data Fusion**: Combine radiographic images with clinical metadata (e.g., patient demographics, symptom scores, biochemical markers) to build holistic predictive models.
4) **Cross-Dataset Validation**: Validate model generalizability on diverse datasets such as the Osteoarthritis Initiative (OAI) and Multicenter Osteoarthritis Study (MOST), ensuring robustness across different imaging equipment, populations, and clinical settings.
5) **Temporal and Longitudinal Modeling**: Develop models that can analyze longitudinal imaging series to predict disease progression and treatment response over time.
6) **Edge Deployment and Real-Time Inference**: Optimize lightweight models like MobileNet for deployment on mobile and embedded devices to facilitate point-of-care diagnostics, especially in resource-limited environments.
7) **Automated Segmentation Integration**: Incorporate automated joint segmentation to focus analysis on regions of interest, potentially improving model precision and reducing background noise.

B. Closing Remarks

In conclusion, this research underscores the transformative potential of deep learning to revolutionize knee osteoarthritis diagnosis by providing accurate, fast, and interpretable severity classification. By continuing to address current limitations and exploring advanced modeling and deployment strategies, future systems can better support clinicians, improve patient outcomes, and facilitate large-scale epidemiological studies.

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