

Hybrid neural network classification of knee osteoporosis using X-ray images and clinical features

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ABSTRACT

Osteoporosis is a degenerative disease marked by decreased bone density and increased fracture risk, particularly in the knee. Early detection is crucial, but conventional diagnostic methods are often subjective and require specialized skills. This study developed an artificial intelligence (AI) model for automatic osteoporosis classification using a hybrid method combining knee X-ray images and clinical data, integrating a convolutional neural network (CNN) for image features with an artificial neural network (ANN) for tabular data. The dataset comprised 239 patients with knee X-ray images and 27 clinical parameters. Pre-processing included handling missing values, encoding, and selecting the 20 best features via the analysis of variance (ANOVA) F-test, with T-score as the most influential parameter. Contrast-limited adaptive histogram equalization (CLAHE) improved image quality, while the synthetic minority oversampling technique (SMOTE) and image augmentation produced a balanced dataset of 462 samples. The hybrid model achieved 97.87% accuracy in classifying normal, osteopenia, and osteoporosis cases. Benchmarked against five alternative backbones (residual network (ResNet) 50V2, densely connected convolutional network (DenseNet) 121, mobile network (MobileNet) V2, vision transformer (ViT), and swin transformer) under the same framework, only the swin transformer matched this performance, while the others reached 74.47–82.98% accuracy, confirming the proposed backbone's contribution. These results show that combining imaging and clinical data improves diagnostic accuracy and supports AI-based early detection in orthopedics.

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1. INTRODUCTION

Osteoporosis is a degenerative disease characterized by a decrease in bone density and quality, which significantly increases the risk of fractures, especially in the knee joints, as the main support for body weight [1]–[4]. This condition has become a global health problem with a prevalence of more than 200 million people, according to the World Health Organization (WHO) [5], [6], and continues to increase with the aging population, especially in postmenopausal women [7]. In Indonesia, the incidence of osteoporosis is projected to increase due to lifestyle changes and an aging demographic structure [8]. Serious clinical impacts, such as a decline in quality of life, long-term disability, and a substantial economic burden, make osteoporosis a priority in health care [9]–[11].

Early detection of osteoporosis in the knee bones is crucial to prevent complications and enable timely therapeutic intervention [12]. However, conventional diagnostic methods have significant limitations.

The interpretation of conventional radiographs is highly dependent on the subjectivity of the radiologist, resulting in variability in diagnosis between observers [13]. Meanwhile, dual-energy X-ray absorptiometry (DEXA) as the gold standard, has limitations in accessibility and relatively high costs, especially in developing countries, thereby hindering mass screening efforts [14]. These limitations drive the need for consistent, efficient, and accurate automated methods to support the early diagnosis of osteoporosis.

Rapid advances in artificial intelligence (AI), particularly deep learning, have opened up great opportunities for the automation of bone disease detection through medical image analysis [15]–[17]. Convolutional neural networks (CNNs) are effective in extracting hierarchical visual features from X-ray images to detect bone structure abnormalities [18], [19]. However, image-based approaches alone ignore important contextual information from the patient's clinical profile, such as age, gender, body mass index (BMI), T-score, and medical history, which have significant diagnostic value in assessing osteoporosis risk [20], [21]. Integrating these two sources of information has the potential to produce more accurate and comprehensive prediction models.

This study aims to develop a multimodal osteoporosis classification framework that integrates knee X-ray images with patient clinical features using a CNN-artificial neural network (ANN) hybrid model. Unlike conventional approaches that rely solely on images, the proposed model is capable of performing three-class classification (normal, osteopenia, and osteoporosis) in a more holistic and clinically relevant manner. The main contributions of this study include: i) the development of a multimodal hybrid model for knee osteoporosis classification; ii) systematic selection of clinical features using the analysis of variance (ANOVA) F-test to identify the most predictive parameters; iii) implementation of a robust pre-processing strategy combining contrast-limited adaptive histogram equalization (CLAHE), geometric augmentation, and synthetic minority oversampling technique (SMOTE) to address image quality variability and class imbalance; and iv) comprehensive validation of the model using various evaluation metrics to ensure accuracy and performance stability. The results of this study are expected to contribute to the development of an AI-based early detection system for osteoporosis that is technically accurate and practically implementable in clinical settings to support faster, more objective, and consistent diagnosis.

2. RELATED WORKS

Research on osteoporosis detection has advanced rapidly with the use of machine learning and deep learning. In general, the approaches used can be grouped into two main categories. These categories are image-based and clinical data-based.

2.1. Image-based approach

Kuo *et al.* [22] developed a combined vision transformer (ViT) and CNN model to detect osteoporosis using low-dose computed tomography (LDCT) images. This model achieved high accuracy (up to 98.7–100% on independent test data) and provided visualizations to improve interpretability. Its advantage lies in its ability to capture global and local features simultaneously. However, this approach does not integrate clinical data and relies on the LDCT modality, which is not always available. Naguib *et al.* [23] proposed a transfer learning-based deep learning model (AlexNet and residual network (ResNet) 50) for three-class classification (normal, osteopenia, and osteoporosis) of knee X-rays, achieving 79–85% accuracy. This approach is clinically relevant because it uses multi-class classification. However, the model does not consider clinical factors such as age and BMI, and its performance is still below 90%.

2.2. Clinical data-based approach

Siddharth *et al.* [24] developed a random forest (RF) model based on clinical data and quantitative ultrasound (QUS) scores with an accuracy of 88%. This approach is more economical and suitable for initial screening, especially in areas with limited facilities. However, this method does not utilize visual information from medical images. Chen *et al.* [25] applied feature selection using least absolute shrinkage and selection operator (LASSO) and Shapley additive explanations (SHAP) interpretation for knee osteoarthritis prediction, resulting in an area under the curve (AUC) of up to 0.96. This study excels in feature selection and interpretability, but it does not integrate medical image data and focuses on osteoarthritis rather than osteoporosis.

2.3. Synthesis of gaps and research position

Image-based approaches excel in visual feature extraction but ignore the clinical context. Conversely, clinical data-based approaches do not utilize structural information from medical images. To date, comprehensive integration between knee X-rays and clinical data in a multimodal framework remains limited. This study proposes a multimodal CNN-ANN hybrid model with a late fusion strategy to combine image features and clinical data. This approach enables optimal processing of each modality, improves

interpretability, and is more suitable for medical data characteristics such as limited dataset size and class imbalance. With this strategy, the model is expected to provide better accuracy and stability compared to unimodal approaches.

3. METHOD

This study proposes a multimodal hybrid method for classifying osteoporosis in the knee bone that combines clinical data and X-ray images within an integrated framework. The developed method consists of five main interrelated stages: data collection, data preprocessing, feature selection, hybrid model development, and model evaluation. Each stage is carefully designed to address specific challenges in osteoporosis classification and maximize model accuracy and generalizability. Figure 1 shows a comprehensive flowchart of the research methodology.

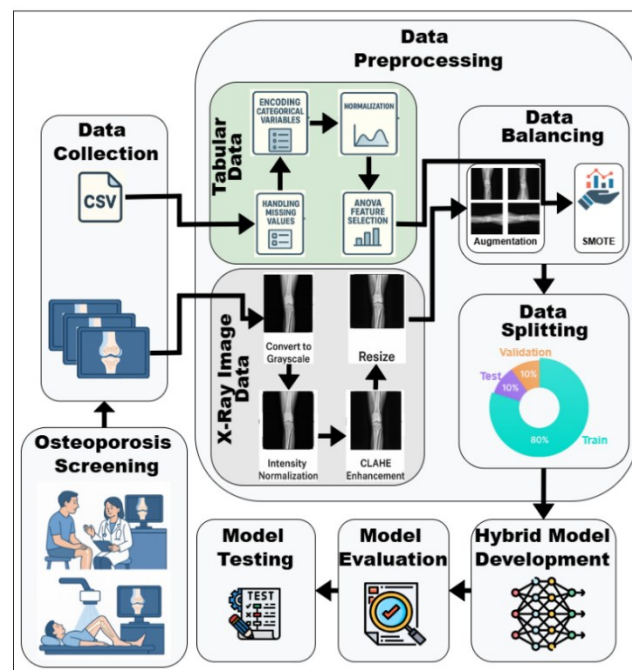


Figure 1. Flowchart of the research methodology

3.1. Dataset collection and characterization

The dataset used in this study was obtained from the publicly available Mendeley data repository, ensuring the reproducibility and transparency of the research. The dataset consists of two main components, namely patient clinical data and knee X-ray images. The clinical data component includes 27 parameters from 239 patients (S. No 1 – 239) that have been medically curated and validated. The distribution of diagnoses shows that 36 patients (15.1%) were classified as normal, 154 patients (64.4%) as osteopenic, and 49 patients (20.5%) as osteoporotic. Almost all patients experienced joint pain (99.2%), with a relatively balanced gender distribution between males (45.2%) and females (54.8%). The age range of patients was 17 – 107 years, with 34.7% of female patients having menopause age data (28 – 57 years).

Anthropometric parameters showed height ranging from 1.37 – 1.83 m, weight 39 – 98 kg, and BMI between 16.1 – 42.8, covering the categories of underweight (0.8%), normal (33.5%), overweight (37.7%), and obese (28.0%). Lifestyle factors showed that 17.2% of patients were smokers and there were no patients with a history of alcohol consumption. Comorbidities included diabetes (5.0%), hypothyroidism (14.2%), seizure disorders (3.3%), and one patient with a history of dialysis. A total of 30.1% of patients had a history of bone fractures, and 27.6% had a family history of osteoporosis. Additional parameters recorded included number of pregnancies (1 – 7 times), estrogen use (4.6%), maximum daily walking distance (0.1 – 10 km), eating habits (more than 10 categories), and more than 30 documented medical history conditions.

The main diagnostic parameters showed T-scores ranging from –2.99 to –0.16 and Z-scores ranging from –2.99 to 0.73, which formed the basis for classification according to WHO criteria. All image data used

came from the same anatomical location, namely the knee (100%), thus ensuring consistency in image-based analysis. The image data components consist of diagnosed knee bone X-ray images grouped into three classes according to WHO criteria, as shown in Figure 2: normal (15.1%), osteopenia (64.4%), and osteoporosis (20.5%). This unbalanced distribution reflects the actual clinical prevalence and poses a methodological challenge that is addressed in the pre-processing stage.



Figure 2. Example of knee X-ray image data

3.2. Data preprocessing

Clinical data preprocessing was performed in several stages. The first step is to handle missing values in clinical data. For numerical data, the mean imputation method is used, while for categorical data, mode imputation is used. This step ensures that there are no empty values that could interfere with the model training process. Next, non-numeric variables are converted into numeric representations through coding tailored to the data type: binary variables are converted using binary encoding, variables with many categories use one-hot encoding, and diagnosis variables use label encoding. After encoding, the numerical data is normalized using min-max scaling to the range $[0, 1]$ to speed up convergence and ensure that features do not dominate the learning process.

To select the clinical features that most influence the diagnosis of osteoporosis, the ANOVA F-test method is used. This process produces the 20 best features from the initial 27 features that have a significant correlation with the T-score value. Algorithm 1 summarizes the clinical data pre-processing steps.

Algorithm 1. Clinical data preprocessing

Input: Raw clinical data D with 27 features

Output: Processed clinical data D' with 20 selected features

1. For each feature f in D :
 - a. If f contains missing values:
 - If f is numeric: impute with the mean
 - If f is categorical: impute with mode
2. For each feature f in D :
 - a. If f is binary: apply binary encoding
 - b. If f is multiple categorical: apply one-hot encoding
 - c. If f is a diagnosis: apply label encoding
3. Normalize all numeric features with Min-Max scaling to $[0, 1]$
4. Calculate the ANOVA F score for each feature against the target
5. Select the 20 features with the highest ANOVA F scores
6. Return D'

Image data preprocessing was carried out; subsequently, preprocessing of knee X-ray images was performed in several stages. First, images are converted from red, green, blue (RGB) to grayscale to simplify the information and improve focus on bone structures. Next, pixel intensity is normalized to a scale of $[0, 1]$ to make pixel values more consistent. CLAHE is applied with a clip limit of 2.0 and an 8×8 tile grid to enhance image contrast, especially in low-brightness bone areas. CLAHE is chosen for its ability to enhance local contrast without over-amplifying noise. Finally, the image is resized to 128×128 pixels to reduce

computational complexity and ensure consistent input dimensions. Algorithm 2 summarizes the image preprocessing steps.

Algorithm 2. Image data preprocessing

Input: Knee X-ray image I (RGB)

Output: Processed image I'

1. Convert I from RGB to grayscale: I_gray
2. Normalize pixel intensity to $[0, 1]$:

$$I_norm = (I_gray - \min(I_gray)) / (\max(I_gray) - \min(I_gray))$$
3. Apply CLAHE with clip limit = 2.0 and tile grid = 8×8 :

$$I_clahe = \text{CLAHE}(I_norm)$$
4. Resize I_clahe to 128×128 pixels:

$$I' = \text{resize}(I_clahe, 128 \times 128)$$
5. Return I'

Data balancing was implemented to address the imbalance in sample size between diagnostic classes, and a data balancing strategy was applied using two complementary techniques. SMOTE was used to increase the sample size in the minority class in clinical data by generating synthetic samples based on k-nearest neighbors interpolation. For image data, augmentation was applied with rotation transformation ($\pm 15^\circ$), horizontal flipping, and brightness adjustment ($\pm 20\%$) using ImageDataGenerator from Keras. The combination of these two techniques produced a balanced dataset with a total of 462 samples, with a relatively even distribution among the three classes. This step ensures that the model is not biased towards the majority class and can learn patterns that are representative of all classes. In the final stage, the dataset was divided into three subsets: 80% training data (370 samples), 10% validation data (46 samples), and 10% testing data (46 samples). This division ensures that the model is trained optimally, verified during the training process to prevent overfitting, and tested on unseen data to objectively measure the model's generalization ability.

3.3. Hybrid model development

This study developed a multimodal hybrid classification model that integrates two different data sources: knee X-ray images and patient clinical data. The architecture of the developed CNN-ANN hybrid model is shown in Figure 3. This model consists of two main branches: CNN for X-ray image processing and ANN for clinical data processing, which are then combined at the fusion layer stage to produce the final prediction.

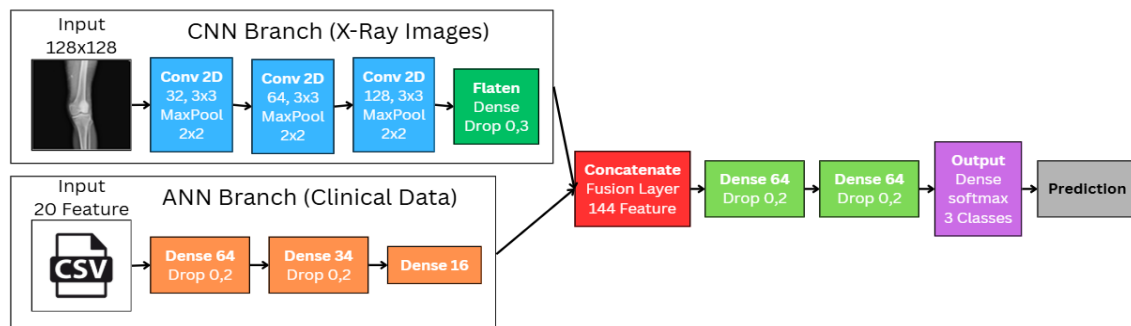


Figure 3. Architecture of the CNN-ANN hybrid model

The CNN branch is used to extract visual features from 128×128 pixel knee X-ray images. The architecture consists of three sequential convolution blocks: Conv2D (32, 64, and 128 filters; 3×3 kernel; rectified linear unit (ReLU) activation), each followed by MaxPooling2D (2×2). The output is then flattened and passed to a Dense 128-neuron layer (ReLU) with dropout 0.3 to reduce overfitting. This configuration was chosen to balance feature extraction capacity and computational efficiency. The ANN branch processes 20 selected clinical features using three fully-connected layers: dense 64, 32, and 16 neurons (ReLU), with dropout 0.2 on the first two layers. Lighter regularization is used because tabular data is more structured than images. Features from both branches are combined through concatenation (late fusion), resulting in a

144-dimensional multimodal vector (128 image features + 16 clinical features). This vector is processed through two dense layers (64 and 32 neurons, ReLU), then a final dense layer of 3 neurons with softmax activation for three-class classification: normal, osteopenia, and osteoporosis based on T-score values. The model uses categorical cross-entropy as the loss function and the Adam optimizer (learning rate 0.001). Training is performed for up to 100 epochs with a batch size of 32 and early stopping (patience = 10) based on validation loss to prevent overfitting.

4. RESULTS AND DISCUSSION

4.1. Model evaluation results

Model performance was evaluated using five comprehensive key metrics: accuracy, precision, recall (sensitivity), F1-score, and AUC. These metrics were chosen because they provide different but complementary perspectives on model performance. Accuracy measures the proportion of correct predictions overall, precision measures the accuracy of positive predictions, recall measures the model's ability to detect all positive cases, F1-score is the harmonic mean of precision and recall that provides a balance between the two, while AUC measures the model's ability to distinguish between classes based on the receiver operating characteristic (ROC) curve. To assess the contribution of the chosen backbone, the main model was benchmarked on the test set against five alternative CNN-ANN and transformer-ANN hybrid configurations trained for up to 100 epochs with the same early-stopping criterion. Table 1 shows the resulting performance of all six models.

Table 1. Model performance evaluation results

Model	Epoch	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
CNN-ANN hybrid (proposed model)	35/100	97.87	96	96	96	100
CNN-ANN hybrid (ResNet50V2)	31/100	78.72	83.45	78.72	78.13	94.48
CNN-ANN hybrid (densely connected convolutional network (DenseNet) 121)	20/100	82.98	85.76	82.98	82.36	93.41
CNN-ANN hybrid (mobile network (MobileNet) V2)	22/100	74.47	78.96	74.47	72.48	93.01
ViT-ANN hybrid	55/100	95.74	95.74	95.74	95.74	99.73
Swin-ANN hybrid (Swin transformer)	45/100	97.87	98.00	97.87	97.87	100.00

Table 1 shows the main model, CNN-ANN hybrid (proposed model), achieved the best overall performance: 97.87% accuracy, 96% precision/recall/F1-score, and 100% AUC in only 35 epochs. Swin-ANN hybrid matched its accuracy/AUC (needing 45 epochs), and ViT-ANN hybrid performed well (95.74% accuracy, 55 epochs), while ResNet50V2, DenseNet121, and MobileNetV2 trailed considerably (74.47 – 82.98% accuracy). This confirms the proposed backbone's compound scaling extracts more discriminative bone-density features than other CNN backbones, while remaining more parameter-efficient than the transformer-based alternatives.

Figure 4 compares the training and validation performance of the six models. Figure 4(a) shows the proposed model, followed by ResNet50V2 in Figure 4(b), DenseNet121 in Figure 4(c), MobileNetV2 in Figure 4(d), ViT-ANN in Figure 4(e), and swin-ANN in Figure 4(f). The proposed model and swin-ANN hybrid exhibit the closest train-validation agreement, with validation loss falling smoothly below 0.1 and minimal overfitting; ViT-ANN hybrid is similarly stable over a longer horizon. In contrast, ResNet50V2, DenseNet121, and especially MobileNetV2 show noisier validation curves that plateau higher or rise again, consistent with their weaker test-set scores. Figure 5 presents the ROC curves, where the proposed model and swin-ANN hybrid hug the top-left corner (AUC = 1.000), followed closely by ViT-ANN hybrid (0.999). The CNN comparators fall further away, with DenseNet121 (0.931) and MobileNetV2 (0.905) showing the widest gap, confirming a reduced ability to discriminate osteopenia from osteoporosis.

Figure 6 shows the confusion matrices. The main model and swin-ANN hybrid misclassified virtually no samples, and ViT-ANN hybrid made one error, while ResNet50V2, DenseNet121, and MobileNetV2 repeatedly confused osteopenia with osteoporosis, misclassifying roughly half to two-thirds of the osteoporosis samples. Since these classes differ mainly by a T-score threshold around -1.0, this indicates the weaker backbones extract less fine-grained bone-density information than the proposed backbone and swin transformer.

4.2. Model testing results

The testing phase was conducted to evaluate the model's ability to identify osteoporosis in previously unobserved data. Knee X-ray images and patient clinical parameters that had not been used in training or validation were used in this testing process. Figure 7 shows the test results on ten test patient

image samples. The model can accurately classify knee bone images into three diagnostic categories with a high confidence level. Four images were predicted as normal with confidence levels between 89.9% and 100%, one image was predicted as osteopenia with a confidence level of 100%, and five images were predicted as osteoporosis with confidence levels between 89.9% and 100%. These test results prove that the CNN-ANN hybrid model is capable of classifying osteoporosis with high accuracy, stability, and good consistency between training data and new data. The high confidence level ($> 89\%$) indicates that the model has strong confidence in its predictions, which is important for clinical applications.

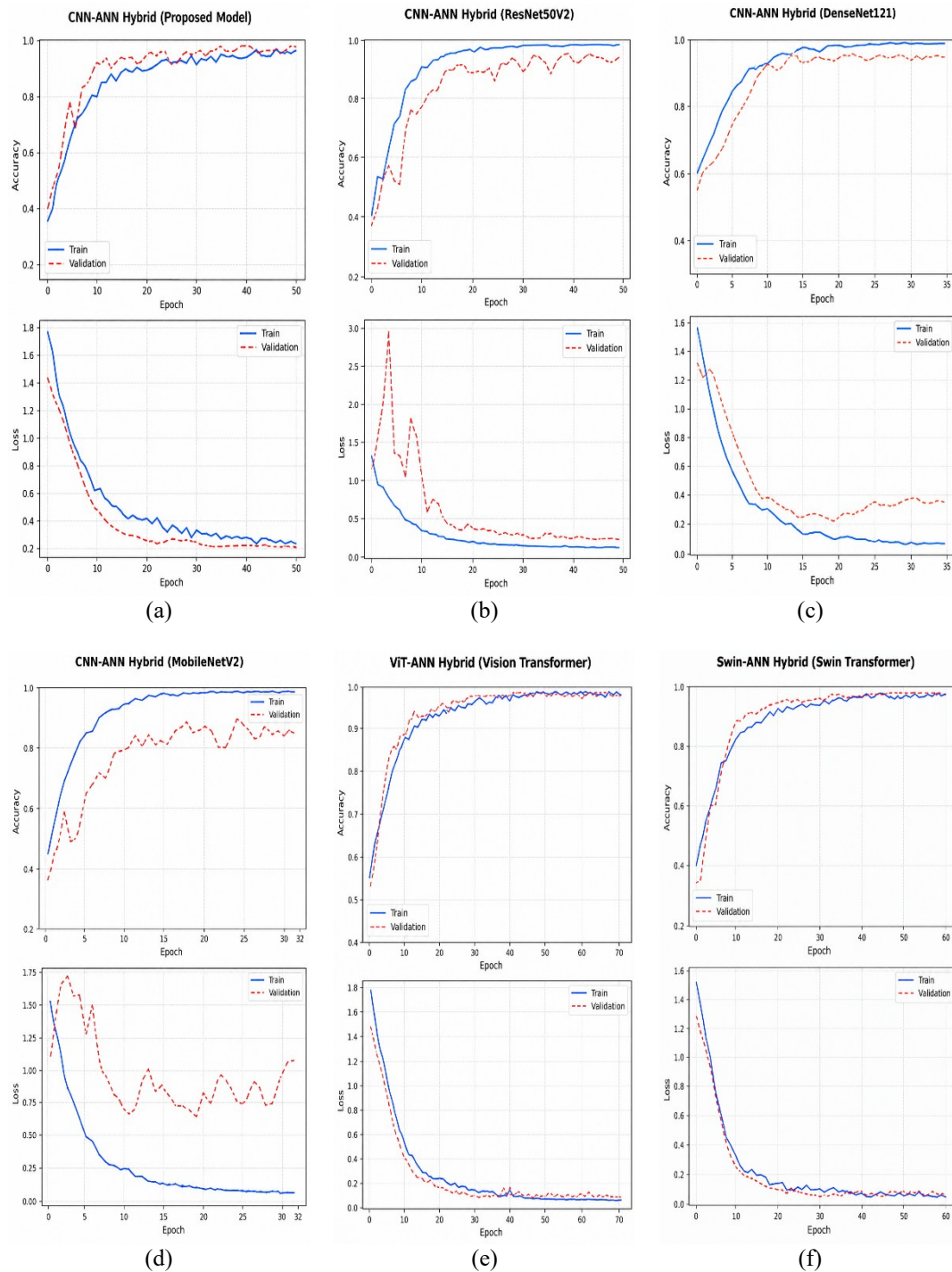


Figure 4. Training and validation performance of (a) proposed model, (b) ResNet50V2, (c) DenseNet121, (d) MobileNetV2, (e) ViT, and (f) swin transformer

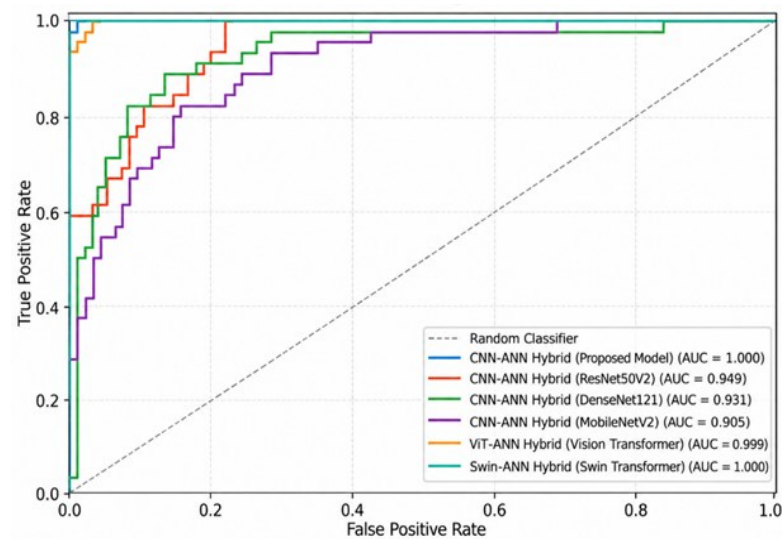


Figure 5. ROC curves of the six compared models

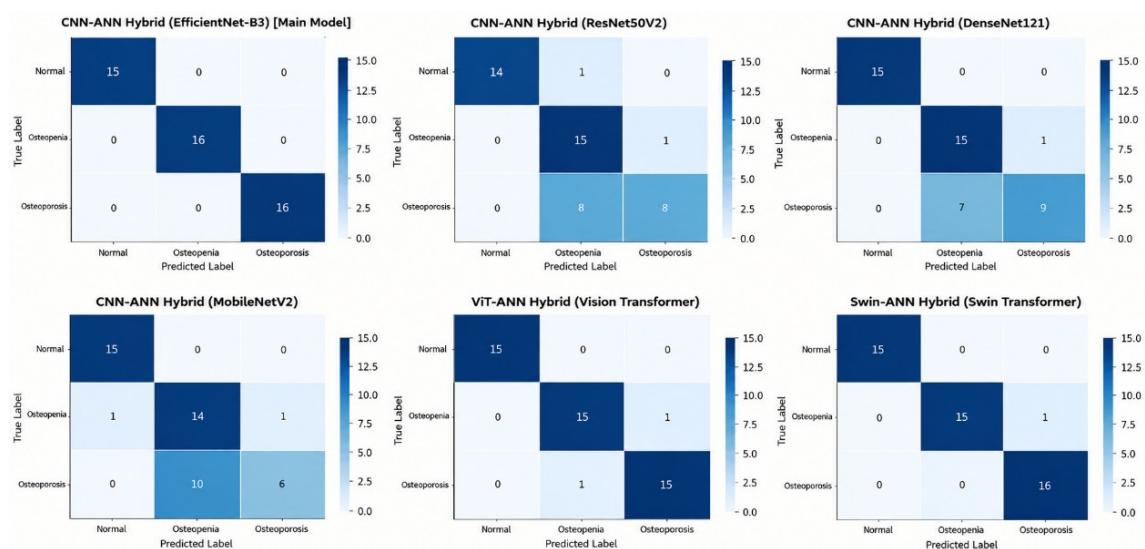


Figure 6. Confusion matrices of the six models on the test set



Figure 7. Model classification results on 10 test samples

4.3. Discussion

Interpretation of results shows that the high performance of the CNN–ANN hybrid model (97.87% accuracy and 100% AUC) was influenced by several key factors. First, multimodal integration allowed the utilization of complementary information between the visual features of the X-rays and the clinical context of the patients. Second, comprehensive pre-processing (CLAHE and SMOTE) improves data quality and balance. Third, the late-fusion strategy allows each modality to be processed optimally before being combined, resulting in more discriminative feature representations. Fourth, ANOVA F feature selection helps reduce noise and improve model efficiency.

Comparison with previous research shows that, compared to the image-based approach by Naguib *et al.* [23] (85.42% accuracy) and the clinical data-based approach by Siddharth *et al.* [24] (88% accuracy), the hybrid model shows a significant performance improvement. Even compared to the ViT + CNN model by Kuo *et al.* [22] (91.6% accuracy), the multimodal approach remains superior. This reinforces that the integration of image and clinical data provides added value compared to unimodal approaches. The internal benchmark against five alternative backbones (Table 1, Figures 4 to 6) further shows that this advantage is not solely due to multimodality: within the same CNN-ANN / ViT – ANN / swin-ANN hybrid framework, only the proposed backbone and swin transformer reached near-perfect scores, while ResNet50V2, DenseNet121, and MobileNetV2 remained well below 90% accuracy. Backbone choice therefore has a substantial effect on final performance, and the proposed backbone offers the best accuracy-to-complexity trade-off among the backbones tested.

Trade-offs and critical analysis show that, the hybrid model has higher complexity (± 2.3 million parameters) and 1.5 – 2 times longer inference time than a single CNN, but it is still feasible for clinical applications. The AUC value of 100% should be interpreted with caution because the test data size is relatively small (46 samples), which may result in an optimistic performance estimate. External validation on larger and more diverse datasets is essential to ensure generalizability.

Limitations include the relatively small dataset size, the use of a single data source, the lack of comprehensive ablation analysis, and the limited interpretability of the model. The risk of overfitting also needs to be considered despite the use of dropout and early stopping. Implications and future directions suggest that the model has the potential to be applied as a clinical decision support system (CDSS) for screening and early detection of knee osteoporosis. However, this system is supportive and does not replace clinical decisions. Further research is needed to conduct multi-institutional validation, ablation analysis, exploration of alternative fusion strategies, model complexity optimization, and improved interpretability (e.g., through gradient-weighted class activation mapping (Grad-CAM) or SHAP) to increase clinical confidence and implementation readiness.

5. CONCLUSION

This study successfully developed a hybrid CNN–ANN model for osteoporosis classification in the knee bone by integrating X-ray images with 27 clinical parameters from 239 patients. After pre-processing and balancing the data, the model achieved excellent performance, with an accuracy of 97.87%, precision of 96%, recall of 96%, F1-score of 96%, and an AUC of 100%, indicating high accuracy and excellent discriminative ability. The main novelty of this work lies in the multimodal integration of CNN for image feature extraction and ANN for clinical data analysis within a single fusion architecture, which significantly outperformed single-image-based models and five alternative backbones. These findings suggest that the proposed model has strong potential as an AI-based CDSS for the rapid, accurate, and effective detection of knee bone osteoporosis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This section not applicable to this study as the research utilized secondary data from a public repository that has been anonymized, and therefore did not involve direct contact with human subjects.

ETHICAL APPROVAL

This section not applicable to this study as the research utilized secondary data from a public repository and did not involve direct intervention on human or animal subjects.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the Mendeley Data repository at <http://doi.org/10.17632/fxjm8fb6mw.2>.

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