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An Effective Deep Learning Based Model for the Prediction of Osteoporosis from Knee X-Ray Images

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Abstract: Osteoporosis is a disease, that makes the bone brittle and weak which occurs mainly in elderly and in women who have gone through menopause. More affordable diagnosing systems are needed as the high costs of diagnosis and treatment make them unaffordable. This research introduces a novel deep learning (DL) based model for the early prediction of osteoporosis from knee X-ray images, addressing the critical need for timely diagnosis of this bone disease. Utilizing a ResNet50-GRU hybrid architecture, the model effectively captures both spatial and temporal relationships within the X-ray data, obtaining remarkable results with 95.65% precision, 95.32% accuracy, 95.98% recall, and 95.49% F1-score. The suggested model demonstrates robust performance in classifying osteoporosis and normal cases. Through extensive evaluation on a dataset of knee X-ray images, this research contributes a powerful tool for healthcare professionals to enhance early osteoporosis detection, potentially improving patient outcomes and reducing associated healthcare costs.

Keywords: *Osteoporosis, Deep learning, ResNet 50, Knee X-ray images, Gated Current Unit (GRU)*

1. Introduction

Osteoporosis is caused due to reduced bone mass and structural deterioration as shown in figure 1. Older adults, especially those who have gone through menopause, may have pain, fractures, musculoskeletal illness, and even death as a result of reduced bone mineral density [1]. Fractures of the distal forearm, hip, humerus, pelvis, vertebrae, etc. are caused by osteoporosis. Osteoporosis comes in two types: primary and secondary. There are two forms of primary osteoporosis: Type I and Type II [2]. These divisions are predicated on the elements that lead to osteoporosis. When osteoporosis reaches the extremely advanced stage where bones are at risk of breaking, symptoms become more noticeable and are therefore known as the “silent disease”. The costs of treating osteoporosis, including fracture repair, deplete the economy's budget significantly. Therefore, a diagnosis must be made early in order to lower treatment costs [3].

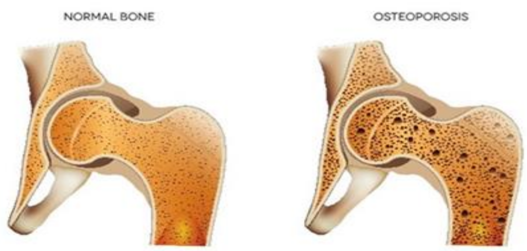

Fig.1. Normal bone and osteoporosis bone

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Various techniques are employed for osteoporosis detection. It was predicted that by 2050, there will be 6.26 million hip fractures globally, up from 1.66 million in 1990 based on population demographic statistics [4]. Therefore, early diagnosis is preferred in order to provide appropriate treatment. The bone mineral density T-score has been recommended by WHO [5] as a means of differentiating between osteoporotic and normal bone: Normal bone is indicated by T-score = −1, osteopenia is indicated by T-score = −1 and −2.5, and osteoporosis is indicated by T-score ≤ −2.5. as shown in figure 2 [6]. By evaluating the mineral density of bones, Dual-energy X-ray Absorptiometry (DXA) is the gold standard in medical terminology for the diagnosis of osteoporosis. DXA is a two-dimensional imaging technology that generates X-ray-like scans and can scan the entire body. In the recent days, due to the advent of modern imagining modalities, the detection of disease was easy and accurate [7].

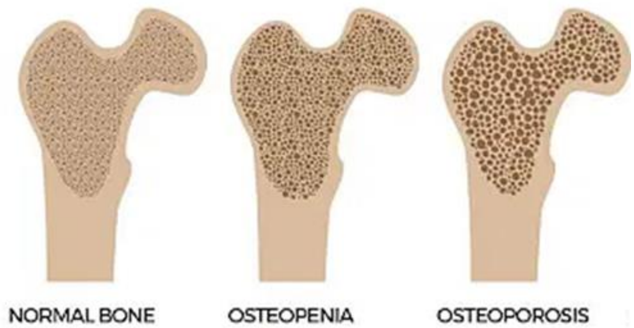


Fig.2. Stages of Osteoporosis

The most widely used imaging method in the medical field to identify bone diseases is X-ray imaging. The earliest and most widely used method for taking images of almost every bone in the body, including the wrist, elbow, shoulder, spine, knee, pelvis, etc [8]. X-ray Imaging is useful in the diagnosing of infections, arthritis, bone injuries, unusual growth of bones, fractures, and joint dislocations. While most fractures of the bones are accidental, they can also be pathological. Osteoporosis, cancer, or osteogenesis all contribute to the weakening of bones [9].

Convolutional Neural Network (CNN) techniques have become increasingly popular among CAD systems for analyzing medical images because of their cutting-edge results in the identification of numerous diseases from images, including cancer detection, pneumonia, brain tumors, and breast cancer [10]. The most frequently stressed joint is the knee, which also has to support the body's weight and allow for movement as shown in Figure 3.

Fig.3. Knee X-Rays

As the population increases, fractures causing osteoporosis around the knee become more common, with women more likely to sustain tibial and fibular fractures [11]. About half of all knee fractures are thought to occur in people over the age of 50, and a high death rate of 22% after a year is observed in senior patients with femoral fractures who have reduced function and a lower quality of life. In the knee bone, the frequency of osteoporosis in Figure 4 must be identified early in order to prevent fractures and lower treatment expenses.

Fig.4. Osteoporotic Knee X-rays

The study establishes a knee osteoporosis early detection system by utilizing the power of DL in conjunction with the affordability of X-ray imaging. The method uses the prominent hybrid model of ResNet 50 – GRU for categorizing the images of Knee X-ray. The main contributions of the proposed work are as follows:

- To develop a new DL model using a hybrid architecture for accurate prediction of Osteoporosis.
- To evaluate the performance of proposed model on a dataset of Knee X-ray images.
- To achieve high levels of accuracy, precision, recall and F1 score in the prediction of osteoporosis to ensure model's effectiveness in early detection.
- To establish the proposed DL model as an effective and reliable tool for clinicians and healthcare professionals to enhance the early diagnosis of Knee Osteoporosis.

The rest of the paper is arranged as follows: A review of existing works is given in Section 2, identifying topics that need more investigation. A detailed explanation of the process is provided in Section 3. The results of the suggested strategy are thoroughly discussed in Section 4, along with a comparison of its performance to those of alternative approaches. Finally, the study wraps up in Section 5 with a summary of the results.

2. Literature Review

Mebarkia et al., [12] provide a thorough method that combines deep analysis with handcrafted techniques for osteoporosis detection from X-ray pictures. Using adaptive filter settings adjusted by a bat-inspired algorithm on Gabor-filtered bone texture pictures, the model applies techniques like HOG and LPQ and outperforms state-of-the-art algorithms with an amazing 89.66% accuracy on an osteoporosis database. This AI-based method closes gaps in physicians' competence while improving diagnosis accuracy. The lack of clinical data linkage and reliance on manually created features, however, are possible drawbacks.

Using machine learning (ML), Lee et al., [13] advance the crucial field of osteoporosis prediction in rheumatoid arthritis (RA) patients. They utilize four machine learning algorithms (ML): logistic regression, random forest, XGBoost, and Light GBM, using the KORONA database. Notably, XGBoost achieves the greatest accuracy of 0.682 and the logistic regression model the highest AUC of 0.750. The study finds age, menopause, body mass index, and other crucial risk factors for osteoporosis in people with RA. The study has drawbacks, such as the lack of a different validation dataset and difficulties creating a fracture-prediction model because of the small number of fracture events.

A Dual-Selective Channel Attention Network (DSNet) is proposed by Xue et al., [14] to predict osteoporosis in CT images of the lumbar spine. To enable feature fusion at various scales, the DSNet combines a novel channel attention module into a supervised deep CNN. With an 83.4% prediction accuracy and a 90.0% recall rate on the test set, the model has encouraging results that show it has the ability to help doctors diagnose abnormal bone mineral density. The limited diversity of patient data and the absence of a separate validation dataset are drawbacks, though. Furthermore, the usefulness of the model in resource-constrained situations might be limited due to its reliance on CT images.

Jang et al., [15] address the drawbacks of DXA as a commonly used screening technique by proposing a DL approach for osteoporosis prediction using basic hip radiography. Their VGG16-equipped deep neural network (DNN) obtained 81.2% of overall accuracy with 91.1% sensitivity, and 68.9% specificity by utilizing a dataset of 1001 DXA and accompanying hip radiography images. An accurate performance of 71.8% and an AUC value of 0.700 were verified by external validation. The lack of varied patient data and the use of DXA as the gold standard, which could introduce biases and affect generalizability to larger groups, are potential drawbacks.

A cost-effective osteoporosis prediction system using an enhanced artificial immune system (AIS) is introduced by Periasamy et al., [16] to solve accessibility issues with high-tech diagnostics like DEXA scans, especially for distant populations. With the inclusion of important variables including sex, age, calcium levels, behaviors, and CT scan data, the suggested AIOPS classifier attains an impressive 94% prediction accuracy. The requirement for thorough validation across a range of groups and the use of self-reported data, which could cause heterogeneity, are possible drawbacks, though. Furthermore, the lack of a thorough examination of the AIS model's interpretability in the study raises questions about its transparency and capacity to understand the underlying decision-making process. Also, the study doesn't provide evidence for predicting the possibility of future fractures.

Jiang et al., [17] describe a novel method for detecting osteoporosis, a significant factor in problems following spinal surgery, utilizing radiomics analysis on lumbar spine CT scans. A signature model using 1040 automatically derived radiomics characteristics performed very well. In the test set, the Hounsfield and radiomics signature models had AUCs of 0.84 and 0.92, respectively Despite these positive results, the study admits many drawbacks, such as its retrospective design, its emphasis on DEXA correlation rather than more general osteoporosis-related issues, and the requirement for extra software operations in the radiomic approach. Larger sample sizes in prospective studies are advised in order to confirm results and investigate uses other than lumbar spine surgery.

In an effort to address the difficulties associated with precisely assessing T-score and bone mineral density (BMD), Fathima et al., [18] introduce a modified U-Net including an attention unit for precise bone segmentation. On the DEXSIT and XSITRAY datasets, the suggested model obtains an accuracy rate of 88%, with Dice scores of 0.94 and 0.92, respectively. The calculated T-score and BMD values are in good agreement with clinical reports, demonstrating how successfully the digitalized X-ray pictures identify osteoporosis. However, regional and texture-based algorithms, as well as classic machine learning algorithms, have limitations to challenge in achieving perfect segmentation and correct classification, which affects the algorithms' overall performance.

Using 2D bone radiograph images, Yousfi et al., [19] used texture analysis and genetic algorithms (GAs) to separate osteoporotic patients from healthy controls. GAs identified the optimum feature combinations by optimizing co-occurrence matrix parameters using texture analysis techniques such as GLCM, RLM, and BSIF. When compared to utilizing GLCM alone (ACC = 77.8%), the

results showed improved classification rates (ACC = 87.50%). The study does, recognize that because of their significant similarity, osteoporosis in X-ray images is difficult to classify. Although GA optimization has been shown to be effective in improving classification rates, there are still issues with computational complexity and resource-intensive needs related to co-occurrence matrices and BSIF approaches.

In an effort to outperform traditional clinical decision tools, Tartibian et al., [20] present a novel method for assessing osteoporosis risk in postmenopausal women using the K-Nearest Neighbors algorithm. It was trained in this 2018 study using data on bone mineral density from Khatam Al-Anbia Hospital and a survey questionnaire. The system performed significantly well in predicting the risk of osteoporosis in the femoral neck, with 61.7% accuracy. The study also recommends customized physical activity depending on a person's unique bone density. Limitations include possible biases in the survey data and the need for confirmation across varied groups, even though the findings aid in the identification of high-risk postmenopausal women.

Keerthika et al., [21] provide an intelligent bio-inspired osteoporosis detection system that uses an artificial immune system-based classifier in conjunction with vibroacoustic bone response. The suggested technique outperforms conventional diagnostic techniques, showing an accuracy of 94% in diagnosing the illness. However, the study's real-world relevance is limited by difficulties with validation and practical implementation. Its actual performance in a variety of clinical circumstances is questionable due to a lack of specific evidence and a comparison analysis with current prediction methods. To determine whether the suggested approach may improve osteoporosis diagnosis, a comprehensive validation process is necessary due to its dependability and flexibility.

3. Materials and Methods

Deep learning is further used for the classification of Osteoporosis. Figure 5, shows an overview of the proposed methodology. The architecture consists of two main components: a pre-trained ResNet50 and a Gated Recurrent Unit (GRU). The obtained images are preprocessed by using the techniques like rescaling and normalization. After augmenting the image data, the images are given as input to the hybrid DL model, thereby by concatenating the outputs, which is subsequently trained and evaluated for performance and finally determined as "Normal" or "Osteoporosis".

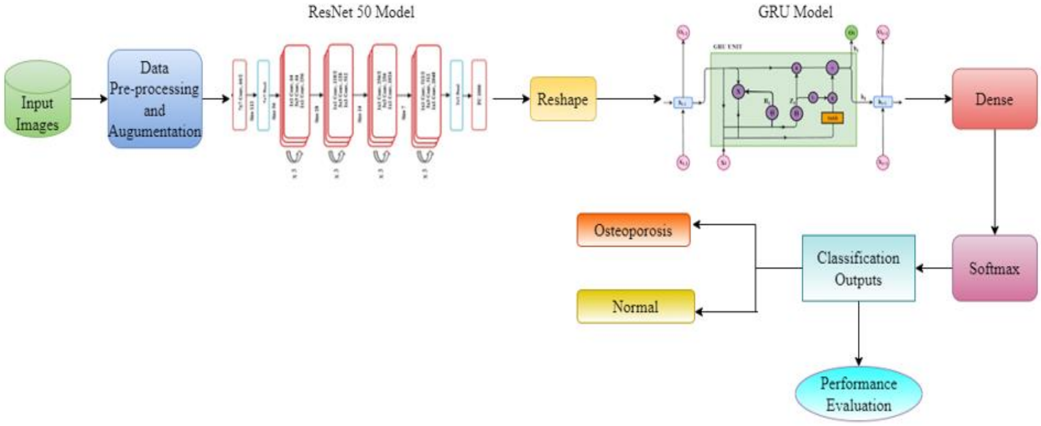


Fig.5. Block diagram of Proposed Methodology

3.1. Dataset

The Knee X-ray image dataset for Osteoporosis was obtained from the Kaggle repository [22]. The dataset consists of two distinct folders having the images of Knee X-ray categorized as Normal and Osteoporosis [23]. Sample images are shown in Figure 6.

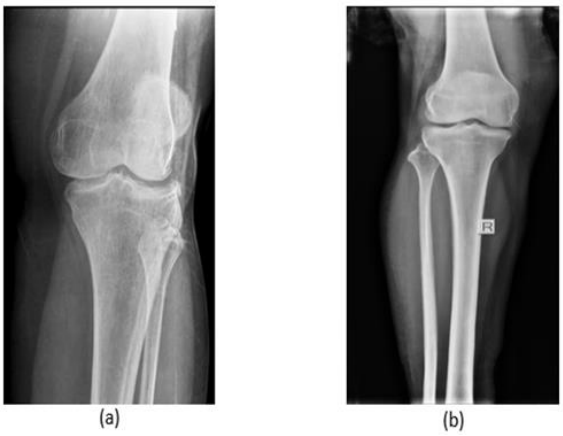


Fig.6. Sample X-ray images of (a) Osteoporosis (b) Normal

3.2. Data Pre-Processing and Augmentation

In image analysis, the preprocessing phase is important since it helps to raise the caliber and reliability of the data. Image preprocessing techniques, including resizing and normalization, were applied before feeding them into the hybrid model. To align with ImageNet pre-trained models, all images were standardized to 224x224 pixels using OpenCV, enhancing efficiency in training. The images underwent a comprehensive normalization process and adjustments to ensure standardized input data in the [0,1] range, essential for subsequent analysis. By making random changes to the initial data, data augmentation is utilized to enhance the size of datasets [24]. The augmented dataset provides options like flipping, altering width and height, and rotation. This approach generates new images with slight alterations, expanding the dataset and enhancing model training by exposing it to a variety of transformations. After augmentation the dataset is divided into training and testing in a 70:30 ratio. The training set ensures comprehensive evaluation, while the test set is exclusively comprised of original images for model training assessment.

3.3. Proposed Methodology

ResNet 50, a deep residual architecture for classification of image is a variant of Residual Network. It uses residual blocks or skip connections to allow information to flow directly from one layer to another. This facilitates the training of very deep networks, as the model can learn residual functions to approximate the underlying mapping more effectively. ResNet50 is a highly parameterized neural network with about 23 million trainable parameters, as seen in figure 7 [25]. It comprises of 50 layers listed as 48 convolutional layers, one max pool and one average pool layers. Every convolution block and every identification block have three convolutional layers. A fully connected layer using a softmax function was connected to the output of the previous block in order to produce the prediction using pre-trained ResNet-50 models improves the capacity to extract high-level representations from input data by utilizing the learnt hierarchical features from a variety of images [26]. In order to efficiently capture both local and global features, the convolutional layers compress the spatial information into a more compact representation. This allows for the integration of the compact representation with other neural network components. It is achieved through the use of global average pooling.

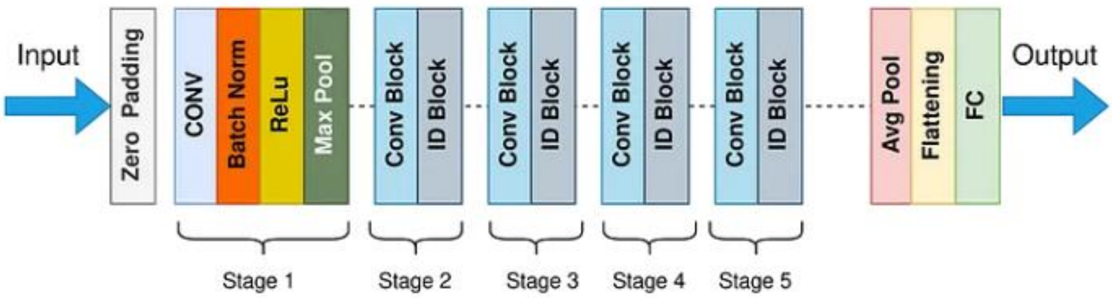


Fig.7. ResNet50 model architecture

The Gated Recurrent Units (GRU) are a gating mechanism in recurrent neural network, and it solves short-term memory problems by combining gating mechanisms in a manner similar to an LSTM. It is less prone to overfitting and easier to train and run. Information flow is controlled and even circulated by an internal mechanism within the GRU known as gates. It is achieved through reset gate and update gate [27]. During processing, the GRU cell receives two inputs such as the input at the current timestamp and the previous hidden state. These are combined by the cell and sent through the reset and update gates. The output in the current timestep is predicted by passing the hidden state through a dense layer with softmax activation by doing this, a new hidden state is created and then transferred to the following time step.

The gates help in determining which information in the GRU cell should be erased or stored. An update gate Z_t is designed by combining input and forget gates. The update gate is in responsible for keeping track of the amount of old memory and fresh data are stored. The hidden layer at the previous timestep, h_{t-1} and the current input, x_t are given as inputs to the update gate. Each has a weight attached to it that is acquired throughout the training process. Also, the update gate's learnable weight is denoted by w_z and the result is obtained as shown in Equation 1.

$$z_t = \sigma(w_z \,.\, [h_{t-1}, x_t]) \tag{1}$$

Reset gates determine what data should be removed from the GRU network by identifying redundant data. The hidden layer at the previous timestep, $h_{t-1}$and the current input, x_t, serve as the reset gate's inputs. Each of them has a weight connected to it that is acquired during training. The output of the update gate r_t is given by Equation 2.

$$\mathrm{r_t} = \sigma\left(\mathrm{w_{r.}}\left[\mathrm{h_{t-1},}\ \mathrm{x_t}\right]\right) \tag{2}$$

A vector that contains the data from previous time steps that are relevant to the current time step is known as the hidden state. It allows the network to choose which data from the previous time step should be kept for the current time step and which should be deleted. The hidden state is calculated from the reset gate. A hyperbolic tangent function is called tanh. It has an output range of (-1,1). In addition, the current cell computed is h_t.

$$\mathrm{h_t} = \tanh(\mathrm{r_t} * [\mathrm{h_{t-1}}, \mathrm{x_t}\ ]) \tag{3}$$

$$\mathrm{h_t} = (1 - \mathrm{z_t}) * \mathrm{h_{t-1}} + \mathrm{z_t} * \mathrm{h_t} \tag{4}$$

Although GRU's architecture is simpler and has shown to be faster and more performance-efficient. Figure 8 depicts the fundamental architecture of GRU.

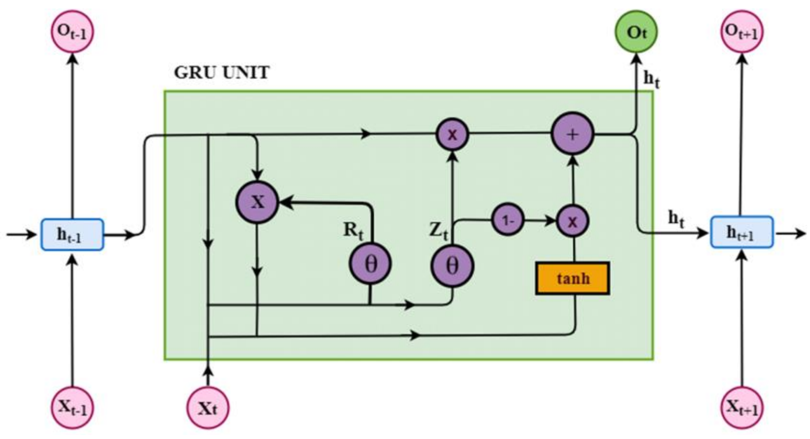


Fig.8. Fundamental Architecture of GRU

The proposed ResNet50-GRU hybrid model represents an innovative approach to Osteoporosis prediction. ResNet50, serving as a deep CNN, acts as a robust feature extractor, proficient in capturing intricate spatial features from knee X-ray data. The model's capacity to identify high-level patterns in the X-ray images is improved by the pre-trained weights on ImageNet. By utilising the knowledge driven from ImageNet the model gains proficiency in interpreting and extracting complex spatial features, contributing its robust performance in identifying relevant patterns and information within the knee X-ray. The GRU model captures both temporal and sequential connections within the dataset enabling accurate prediction. The GRU's step-by-step processing improves the model's overall ability. By systematically analyzing the spatial information extracted by ResNet50, the GRU enhances the model's predictive skills for osteoporosis detection by facilitating a more thorough comprehension of the complex connections found in the knee X-ray images. The hybrid model's addition of a dense layer with softmax activation in the output layer is essential. This dense layer performs the crucial task of making classification easier by producing probabilities for every class, which helps with the precise diagnosis. The algorithm for the proposed model as shown below.

Algorithm

Input: *Knee X-ray images dataset (X), corresponding labels indicating osteoporosis or normal (Y)*
Output: *Predictions for osteoporosis probability for each knee X-ray image*

Begin

- ***Data Preparation***
  - ❖ *Preprocess images: Rescale, normalize, and augment the dataset for enhanced training*
  - ❖ *Split dataset: Divide the pre-processed dataset into training and testing sets (X_train, Y_train, X_test, Y_test)*
- ***Model Building and Training***
  - ❖ *Load pre-trained ResNet50 model with weights from ImageNet*
  - ❖ *Extract spatial features using ResNet50 for each knee X-ray image in X_train and X_test*
  - ❖ *Initialize GRU model to capture temporal dependencies*
  - ❖ *Train GRU using the spatial features obtained from ResNet50 on X_train*
  - ❖ *Combine ResNet50 and GRU models to create the hybrid model*
  - ❖ *Add a dense layer with softmax activation for classification*
  - ❖ *Compile the hybrid model using appropriate loss function and optimizer*
  - ❖ *Train the hybrid model using X_train and Y_train*
- ***Model Evaluation***
  - ❖ *Evaluate the model on X_test and Y_test to assess its performance*
  - ❖ *Calculate metrics such as accuracy, F1-score, recall and precision.*

End

Figure 9 shows the optimized structural diagram of ResNet 50-GRU model. Before training the model, the base architecture has been frozen and its weights are not altered further. The learning rate and weight are adjusted using the Adam optimizer in accordance with loss backpropagation. Binary cross-entropy is utilized in the suggested binary model to compute the loss. Every model has undergone 100 training epochs. The model’s loss and accuracy are regularly observed. Table 1 displays the suggested model’s summary.

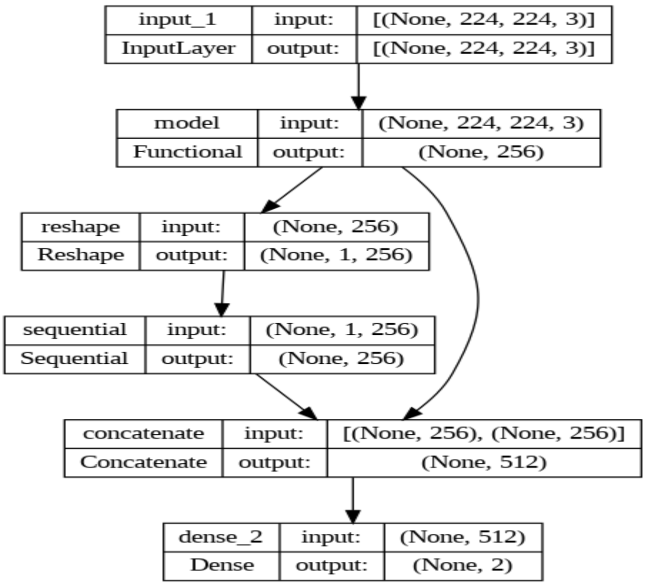


Fig.9. Architecture of the designed model

Table 1. Summary of the designed model

Total Parameters	24297095
Trainable Parameters	24243975
Non- Trainable Parameters	53120

3.4. Evaluation Metrics

Evaluation metrics offer a numerical representation of the model's performance, facilitating to assess its effectiveness in a systematic and objective manner. Table 2 displays some of the important evaluation criteria used in the suggested study.

Table 2. Evaluation Metrics

Evaluation Metrics	**Formulas**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-score	$\frac{2*(Precision*Recall)}{(Precision+Recall)}$
TP-True Positive, TN- True Negative, FP-False Positive, FN-False Negative	

4. Result And Discussion

4.1. Hardware and Software Setup

The system's components for the experimental setup include one NVIDIA GeForce GTX 1080 Ti GPU 2760 4MB and an Intel Core i7-6850K 3.60 GHz 12-core processor. The Google Collaboratory is used as the model implementation platform. As a result, using the predictions the novel framework has been trained and tested. The efficiency of the suggested model was evaluated and algorithms were validated using ground truth data. Hyperparameters of deep neural networks are empirically determined and significantly affect learning that is listed in Table 3.

Table 3. Hyperparameters

Model Parameters	**Values**
Image size	224*224
Optimizer	Adam
Learning Rate	0.001
Loss Function	Binary cross entropy
Batch Size	16
Number of Epochs	100
Activation function	Relu, Softmax

4.2. Experimental Results

The proposed networks were trained on the Knee X-ray images dataset and assessed in order to determine how well they classified Osteoporosis. The suggested framework relying on the ResNet 50-GRU model achieves a highest accuracy of 95.65%, in accordance to the result of the study. The proposed model's accuracy plot and loss plot is shown in Figure 10 and 11. The dataset with 100 epochs was used to train the model. The graph shows that enhanced accuracy is related to increase in the epoch counts. The loss also dropped according to the epochs, attaining its minimum value at the end of training, demonstrating that the framework was properly trained and that classification of Osteoporosis was possible.

Fig.10. Accuracy Plot

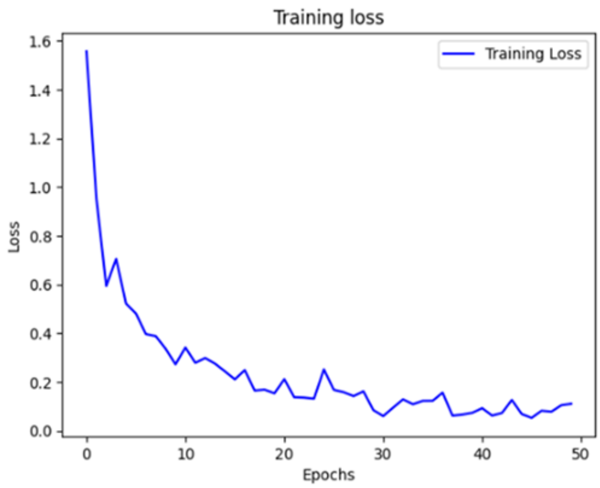


Fig.11. Loss Plot

As shown in Figure 12, The confusion matrix shows the number of images the model classified both correctly and incorrectly. The matrix compares the target and predicted outputs of the classification model.

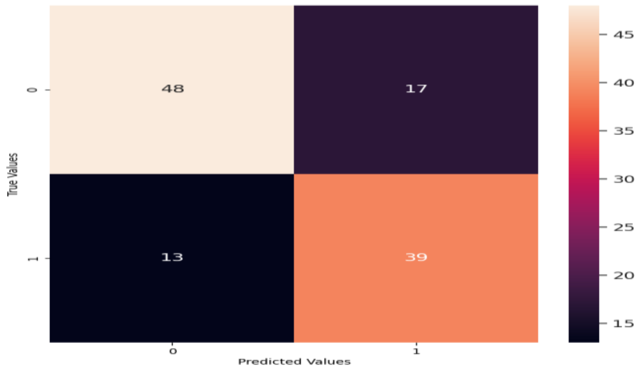


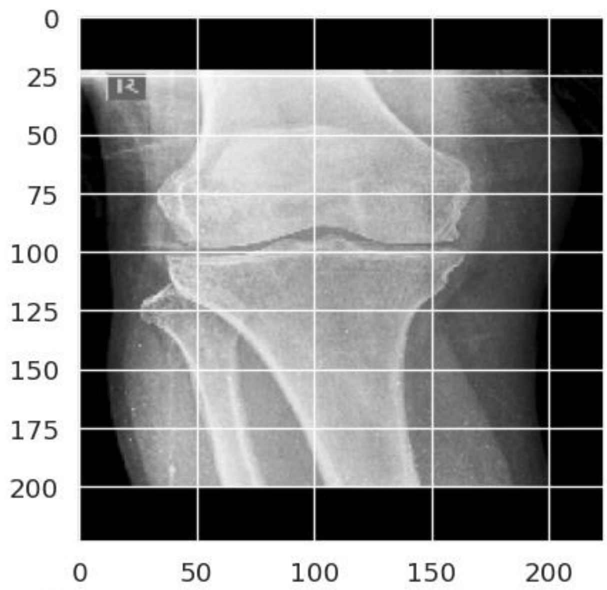
Fig.12. Confusion Matrix

The DL model developed for osteoporosis prediction from images of knee X-ray in Table 4, demonstrates impressive performance metrics. With an accuracy of 95.65%, the model showcases its proficiency in correctly classifying osteoporosis and normal cases. High precision at 95.32% indicates the model's ability to minimize false positives, while an impressive recall of 95.98% emphasizes its capability to effectively identify true positives. The F1-Score of 95.49% further supports the model's robustness, considering both precision and recall. These results underscore the effectiveness of the DL-based approach, highlighting its potential for accurate osteoporosis classification from images of knee X-ray.

Table 4. Proposed Model's Classification Report

Accuracy	95.65%
Precision	95.32%
Recall	95.98%
F1-score	95.49%

From the dataset, a randomly chosen image undergoes classification within the proposed model, accurately identifying as Osteoporosis. This successful classification underscores the effectiveness and reliability of the model in accurately recognizing and categorizing images within the dataset as shown in Figure 13.




```
1/1 [==============================] - 2s 2s/step
osteoporosis
```

Fig.13. Sample Output

Table 5 shows the comparison between the suggested and the current approaches.

Table 5. Comparison of proposed with existing methods

AUTHOR	METHODOLOGY	RESULT
Mebarkia et al., (2023) [12]	Hybrid Feature Extraction with Gabor Filter	• Accuracy: 89.66%
Lee et al., (2023) [13]	Machine Learning Algorithm	• Logistic Regression AUC: 75% • Accuracy XGBoost: 68.2%
Xue et al., (2022) [14]	DSNet	• Prediction Accuracy: 83.4% • Recall: 90%
Periasamy et al., (2022) [16]	Artificial Immune System (AIS) Approach	• Accuracy: 94%
Fathima et al., (2020) [18]	Modified U-Net with Attention unit	• Accuracy: 88%
Tartibian et al., (2020) [20]	Data Mining Algorithm using K-NN	• Accuracy: 61.7%
Proposed Methodology	**Hybrid ResNet 50-GRU**	• **Accuracy: 95.65%** • **Precision: 95.32%** • **Recall: 95.98%** • **F1-Score: 95.49%**

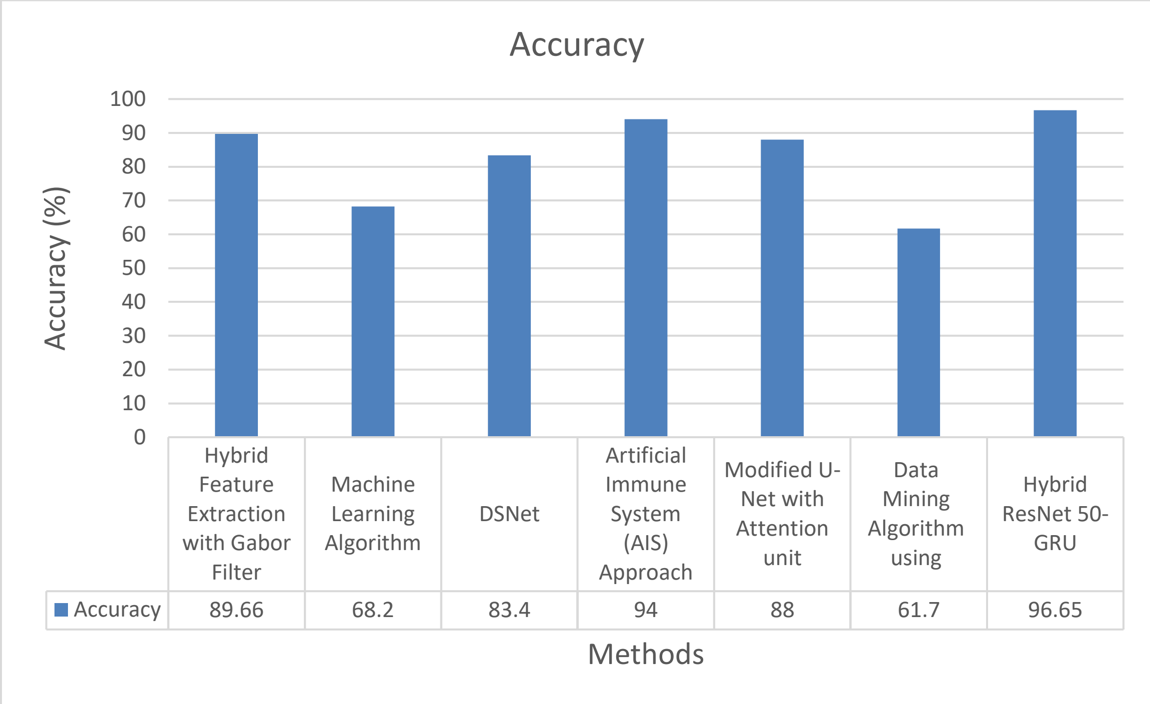


Fig.14. Comparison chart of existing and proposed methods

5. Conclusion

This study develops a novel DL-based model to predict osteoporosis from knee X-ray images, thereby addressing the important issue in osteoporosis diagnosis. Osteoporosis poses significant health risks, and early detection is essential for timely intervention and effective treatment. In order to capture both temporal and spatial relationships within knee X-ray data, the proposed ResNet50-GRU hybrid model combines the advantages of CNNs with gated recurrent units (GRUS). The model achieves remarkable accuracy of 95.65%, precision of 95.32%, recall of 95.98%, and balanced F1-score of 95.49%. The model's ability to classify patients as either osteoporosis or normal is testimony to its efficiency in producing accurate predictions. The study's contributions include the creation of a strong tool for physicians to improve early osteoporosis diagnosis, assessment on a dataset of knee X-ray images, and the creation of an innovative DL model. These results have the potential to enhance healthcare outcomes and reduce the financial burden caused by complications related to osteoporosis.

Conflicts of interest

The authors declare no conflicts of interest.

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