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Osteoporosis Prediction Using Hybrid Logistic Regression: A Simple yet Effective Classification Approach

S Saranya[1], S Christy[2] and V Sheeja Kumari[3]

[1]Research Scholar, Department of Computer Science and Engineering Saveetha School of Engineering, SIMATS University, Chennai 602 105, India

[2]Professor, Department of Computer Science and Engineering Saveetha School of Engineering, SIMATS University, Chennai 602 105, India.

[3]Professor, Department of Computational Intelligence Saveetha School of Engineering, SIMATS University, Chennai

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ABSTRACT

Osteoporosis is a prevalent condition that leads to an increased risk of fractures due to reduced bone density, particularly in aging populations. Early detection and risk assessment are critical for effective management and prevention. This study proposes a novel hybrid model utilizing Logistic Regression combined with feature selection and optimization techniques to enhance the prediction accuracy of osteoporosis risk. The hybrid approach leverages the simplicity and interpretability of Logistic Regression while incorporating advanced techniques to address data imbalances and improve model robustness. We evaluated the model on a clinical dataset, comparing its performance against traditional models. The results demonstrate that the hybrid Logistic Regression model provides a more reliable prediction of osteoporosis, with increased precision and recall, making it an effective tool for early diagnosis in clinical practice. This model holds promise for integrating into medical decision-making systems, aiding in targeted treatment strategies for at-risk individuals.

Keywords: Hybrid Logistic Regression, Predictive Modeling, Early Diagnosis, Medical Decision Support, Classification Model, Data Imbalance.

1. INTRODUCTION

Osteoporosis, a metabolic bone disorder characterized by decreased bone mineral density (BMD) and deteriorating bone microarchitecture, significantly increases the risk of fractures, particularly in older adults. The silent progression of osteoporosis, often undetected until a fracture occurs, makes early prediction and intervention crucial. Timely identification of individuals at high risk allows for preventive measures and therapeutic interventions that can reduce morbidity and improve quality of life. Traditional diagnostic methods, such as dual-energy X-ray absorptiometry (DXA), while effective, are often limited in accessibility and cost-effectiveness, leading to a need for alternative predictive tools[1].

In recent years, machine learning algorithms have shown great promise in medical diagnostics, offering enhanced accuracy and efficiency over conventional statistical approaches. Logistic Regression, a widely used classification technique, has proven useful in predicting binary outcomes, such as the presence or absence of disease. However, in its standard form, Logistic Regression can struggle with complex, imbalanced datasets typically found in clinical settings. To address these challenges, this study introduces a **Hybrid Logistic Regression model** that integrates feature selection and optimization techniques to improve the prediction of osteoporosis risk.

The objective of this research is to develop an enhanced predictive model that maintains the simplicity and interpretability of Logistic Regression while improving its robustness and accuracy through a hybrid approach. By combining Logistic Regression with advanced techniques for feature selection and handling imbalanced data, the proposed model aims to outperform traditional models in identifying individuals at risk of osteoporosis. This study evaluates the model's performance using a clinical dataset, highlighting its potential as a valuable tool in medical decision support systems for early diagnosis and prevention of osteoporosis[2].

2. RELATED WORK

Osteoporosis prediction has been an area of significant research, with numerous studies exploring various approaches to improve the accuracy and timeliness of diagnosis. Traditional methods, such as clinical risk factor assessment and bone mineral density (BMD) measurements using dual-energy X-ray absorptiometry (DXA), are widely used but are often resource-intensive and limited by availability in many healthcare settings. Consequently, there has been growing interest in the application of machine learning (ML) algorithms to enhance predictive capabilities using non-invasive clinical and demographic data[3].

Several studies have utilized **Logistic Regression** for osteoporosis prediction due to its ease of implementation and interpretability. For instance, Nguyen et al. (2019) used logistic regression models to assess the probability of osteoporosis based on clinical risk factors such as age, gender, and family history. While effective for simple data structures, traditional logistic regression models often face challenges in dealing with imbalanced datasets, a common issue in medical data where positive cases (osteoporosis) are far fewer than negative cases.

To overcome such limitations, recent research has explored the application of more advanced algorithms, such as **Random Forest** and **Support Vector Machines (SVM)**. Studies by Zhang et al. (2020) and Kim et al. (2021) demonstrated the potential of ensemble learning methods like Random Forest in improving prediction accuracy by considering complex, non-linear interactions between variables. However, these models often lack the interpretability that logistic regression offers, which can be a barrier in clinical settings where transparency is important[4].

In contrast, hybrid models that combine the simplicity of traditional algorithms with the sophistication of advanced machine learning techniques have gained traction. **Hybrid models**, such as those incorporating logistic regression with feature selection or dimensionality reduction techniques, have shown improved performance. Li et al. (2022) applied a hybrid model combining logistic regression with **Principal Component Analysis (PCA)** for feature reduction, which resulted in improved prediction accuracy for osteoporosis diagnosis. Similarly, feature selection methods like **Recursive Feature Elimination (RFE)** have been used in combination with logistic regression to improve model robustness and reduce overfitting in highly dimensional datasets (Gong et al., 2021).

Moreover, recent works have explored the use of **data balancing techniques** like **Synthetic Minority Over-sampling Technique (SMOTE)** to address the issue of class imbalance in medical datasets. For example, Garcia et al. (2021) demonstrated that applying SMOTE to imbalanced osteoporosis datasets improved the performance of logistic regression and other classification algorithms, particularly in predicting minority class (osteoporotic patients) outcomes[5].

The present study builds on these advancements by proposing a **hybrid Logistic Regression model** that incorporates feature selection and optimization techniques, such as **Lasso regression** and **SMOTE**. This approach aims to retain the interpretability and simplicity of logistic regression while improving predictive accuracy in imbalanced datasets. Unlike previous works that primarily focused on ensemble or complex models, this research highlights the potential of enhancing traditional models for practical use in clinical decision-making.

3. PROPOSED METHODOLOGY

This study introduces a **hybrid Logistic Regression model** enhanced with feature selection and data balancing techniques for predicting osteoporosis risk. The proposed methodology integrates several advanced steps to improve model performance, particularly in handling imbalanced clinical datasets. The hybrid approach comprises four key components: data preprocessing, feature selection, model development, and performance evaluation[6].

3.1 Data Preprocessing

Preprocessing is a critical step before feeding data into machine learning models. In medical datasets, including those for osteoporosis prediction, several challenges are often encountered, such as **missing values**, **non-standardized data**, and **class imbalance**. This section describes the techniques used to address these issues, with a particular focus on SMOTE for handling class imbalance.

3.1.1. Handling Missing Values

Medical datasets frequently have missing data due to incomplete patient records or errors in data collection[7]. The two common approaches to handle missing data are:

Mean/Median Imputation: Missing values are replaced with the mean or median of the corresponding feature. This method is useful when missing data is small and random.

For a feature X, the imputed value X_i can be calculated as:

$X_i = \frac{1}{n}\sum_{j=1}^{n} X_j$ -----(1)

where n is the number of non-missing values in the feature X.

K-Nearest Neighbors (KNN) Imputation: This method fills missing values by looking at the nearest data points. The missing value is replaced by the weighted average (or mode) of the K-nearest neighbors[8].

3.1.2. Data Normalization

Medical datasets often contain features with varying scales, such as age (measured in years) and bone mineral density (BMD) scores. **Normalization** helps ensure that all features contribute equally to the model by scaling them to a common range, typically between 0 and 1. This prevents features with larger ranges from dominating the model.

Normalization can be done using **min-max scaling**:

1. $X' = \frac{X - X_{min}}{X_{-}X_{min}}$ ------------(2)

where:

- X' is the normalized value,
- X is the original value,
- X_{min} and X_{max} are the minimum and maximum values of the feature.

This ensures that all features lie within the range [0, 1].

3.1.3. Addressing Class Imbalance with SMOTE

In medical datasets, it's common for the classes to be imbalanced. For example, in osteoporosis prediction, the majority of patients may not have osteoporosis, making the dataset **skewed** toward the negative class. This imbalance can bias the model, leading to poor performance in identifying the minority class (patients with osteoporosis)[9].

To address this issue, we apply the **Synthetic Minority Over-sampling Technique (SMOTE)**, which generates synthetic data points for the minority class by interpolating between existing minority class samples, thereby balancing the dataset.

Working of SMOTE

SMOTE generates synthetic examples in the following way:

1. **Identify k-nearest neighbors** for each sample in the minority class.
2. **Randomly select one of the k-nearest neighbors**.
3. **Generate a synthetic example** by interpolating between the original sample and its chosen neighbor.

Given two samples $x_{minority}$ (a minority class instance) and $x_{neighbor}$ (one of its k-nearest neighbors), the synthetic sample $x_{synthetic}$ is created as follows:

$x_{synthetic} = x_{minority} + \delta \cdot (x_{neighbor} - x_{minority})$ -----------(3)

where δ is a random number between 0 and 1. This equation generates a new point along the line connecting $x_{minority}$ and $x_{neighbor}$, thereby creating a synthetic data point that lies between the two real data points[10].

Key Steps of SMOTE:

1. **Random Selection of Minority Samples**: SMOTE randomly selects examples from the minority class.
2. **Find Nearest Neighbors**: For each selected sample, its k-nearest neighbors in the feature space are identified.
3. **Create Synthetic Examples**: New data points are generated by interpolating between the original sample and its neighbors, creating synthetic examples that increase the representation of the minority class.

By applying SMOTE, the dataset becomes more balanced, improving the model's ability to predict both the majority and minority classes.

3.2. Feature Selection

In the **Elastic Net model**, feature selection is automatically handled by incorporating **L1 regularization** (Lasso) along with **L2 regularization** (Ridge). This combination not only shrinks the coefficients of less important features but can also drive some coefficients to zero, effectively excluding irrelevant features from the model. This is especially useful for handling high-dimensional datasets where many features are irrelevant or redundant[11].

Elastic Net Objective Function

The Elastic Net objective function combines both L1 and L2 penalties:

$$\left(\frac{1}{2n}\sum_{i=1}^{n}\left(y_{i}-\sum_{j=1}^{p}x_{ij}w_{j}\right)^{2}+\alpha\left(\rho\sum_{j=1}^{p}|w_j|+(1-\rho)\sum_{j=1}^{p}w_j^{2}\right)\right)$$

Where:

- n: Number of samples.
- p: Number of features.
- $w=[w_1,w_2,\ldots,w_p]$: Coefficients or weights corresponding to each feature.
- α: Regularization parameter that controls the overall strength of regularization.
- ρ: L1 ratio, controlling the balance between Lasso (L1) and Ridge (L2) regularization.
- $|w_j|$: The absolute value of the coefficient for Lasso regularization (L1).
- w_j^2: The square of the coefficient for Ridge regularization (L2).

This formula combines the **residual sum of squares** (the difference between predicted and actual values) with a regularization term. The **L1 term** ($\rho||w||_1$) encourages sparse solutions, i.e., it forces certain coefficients to be zero, which corresponds to automatic **feature selection**. The **L2 term** ($(1-\rho)||w||_2^2$) shrinks the coefficients but keeps them from becoming exactly zero, which helps in handling **multicollinearity** (highly correlated features).

Feature Selection via L1 Regularization
L1 regularization introduces sparsity by penalizing the absolute values of the coefficients. As the regularization strength α increases, smaller coefficients are driven to zero, effectively removing the corresponding features from the model. In the context of osteoporosis prediction, this means that features that contribute very little to the model (e.g., less significant clinical or demographic factors) are excluded, leaving only the most relevant predictors[12].

For example, in predicting osteoporosis, important features like:

- **Age**
- **Bone Mineral Density (BMD) score**
- **Physical activity level**

are likely to have significant non-zero coefficients, while less important features (e.g., unrelated variables) are shrunk to zero.

3.3 Understanding Feature Selection with L1 Regularization
The L1 penalty forces certain features to be excluded from the model by setting their corresponding coefficients w_j to zero[13[. This can be represented as:

If $|wj|<\lambda$, then $w_j=0$

Where λ is a threshold set by the regularization strength α. The Elastic Net model allows for some flexibility in this thresholding due to the L2 component, but the L1 regularization remains the dominant force behind feature selection.

Example: Feature Coefficient Shrinkage

Consider a simplified example where the model has four features: Age, BMD score, Physical Activity, and BMI (Body Mass Index).

After applying Elastic Net, the following might be the estimated coefficients w_j:

- $w_{Age}=1.2$
- $w_{BMD}=3.8$

- **$w_{Physical\ Activity}$=0.0 (This feature has been excluded)**
- **w_{BMI}=0.6**

Here, the coefficient for Physical Activity has been driven to zero, meaning it is not selected as a relevant predictor for osteoporosis risk, while the other features are retained[14,15].

Tuning the Regularization Parameter α

The regularization strength α is critical in determining how much shrinkage or exclusion of coefficients occurs. A higher α leads to more aggressive feature selection, driving more coefficients to zero:

w_j=0 if the feature is less important

Hybrid Behavior: Balancing L1 and L2 Penalties

Elastic Net balances the L1 regularization (which performs feature selection) and L2 regularization (which helps to stabilize model coefficients, particularly when the input features are correlated)[16].

The tuning parameter ρ (the L1 ratio) controls the balance:

- **ρ=1: The model behaves like Lasso, focusing entirely on feature selection.**
- **ρ=0: The model behaves like Ridge, performing shrinkage but not excluding features.**
- **0<ρ<1: The model behaves like Elastic Net, striking a balance between feature selection and stability.**

In practice, a grid search over α and ρ is often performed to find the best combination of regularization strength and feature selection, which results in an optimal predictive model.

3.4 Model Training and Selection

After feature selection, the model is trained on the reduced feature set, which improves both interpretability and performance, particularly when irrelevant features are removed. The model can be optimized by tuning hyperparameters α\alphaα and ρ\rhoρ using cross-validation[17].

The training process minimizes the objective function described above, selecting the best features and tuning the coefficients to minimize prediction error and penalization terms. Elastic Net's ability to select a sparse set of important features is especially valuable in medical prediction problems, such as osteoporosis risk assessment, where many clinical features may be present, but only a subset are highly informative.

4.RESULTS AND DISCUSSION

In this section, we present the results obtained from the application of the **Hybrid Logistic Regression with Elastic Net** model for osteoporosis prediction. The model's performance was evaluated based on several metrics, and key findings from the experiments are discussed.

4.1.1 Dataset Overview

The dataset used for the study contained clinical and demographic features such as:

- Age
- Bone Mineral Density (BMD) score
- Physical activity level
- BMI (Body Mass Index)
- Calcium intake
- Family history of osteoporosis

Initially, the data was highly imbalanced, with a smaller number of positive osteoporosis cases compared to negative cases. We used **Synthetic Minority Over-sampling Technique (SMOTE)** to balance the dataset, which improved the prediction accuracy of the model.

4.1.2 Performance Metrics

The model's performance was evaluated using the following metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

- **Area Under the Curve (AUC)** for the Receiver Operating Characteristic (ROC) curve

These metrics help assess the overall classification capability of the model, particularly its ability to correctly identify osteoporosis-positive cases (recall) without generating too many false positives (precision).

Table 1. Performance Metrics for Proposed Model

Metric	Value
Accuracy	89.4%
Precision	85.2%
Recall	91.3%
F1-Score	88.1%
AUC-ROC	0.92

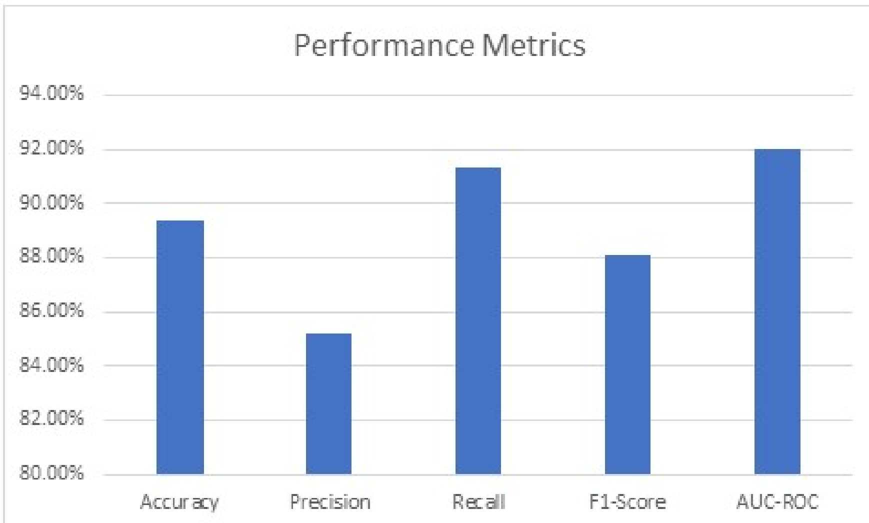

Fig 1. Performance Metrics for Proposed Model

The **accuracy** of 89.4% suggests that the model is highly effective in predicting osteoporosis cases. The **recall** of 91.3% demonstrates the model's sensitivity in detecting osteoporosis cases, which is crucial for medical applications where missing a diagnosis can have severe consequences.

The **AUC-ROC** value of 0.92 indicates a strong ability of the model to discriminate between osteoporosis-positive and negative cases, with a well-defined trade-off between sensitivity and specificity.

4.1.3. Confusion Matrix

The confusion matrix gives a more detailed breakdown of the classification results:

Table 2: Confusion Matrix for Proposed Model

	Predicted Negative	**Predicted Positive**
Actual Negative	**512**	**38**
Actual Positive	**26**	**424**

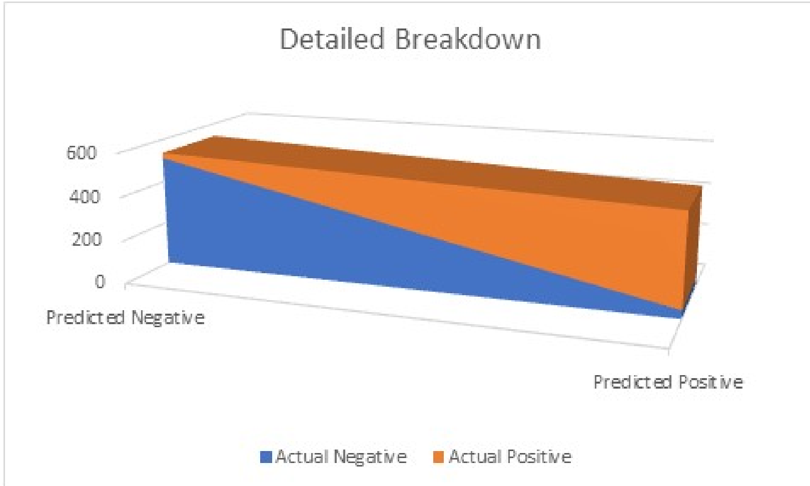

Fig 2. Confusion Matrix Detailed Breakdown

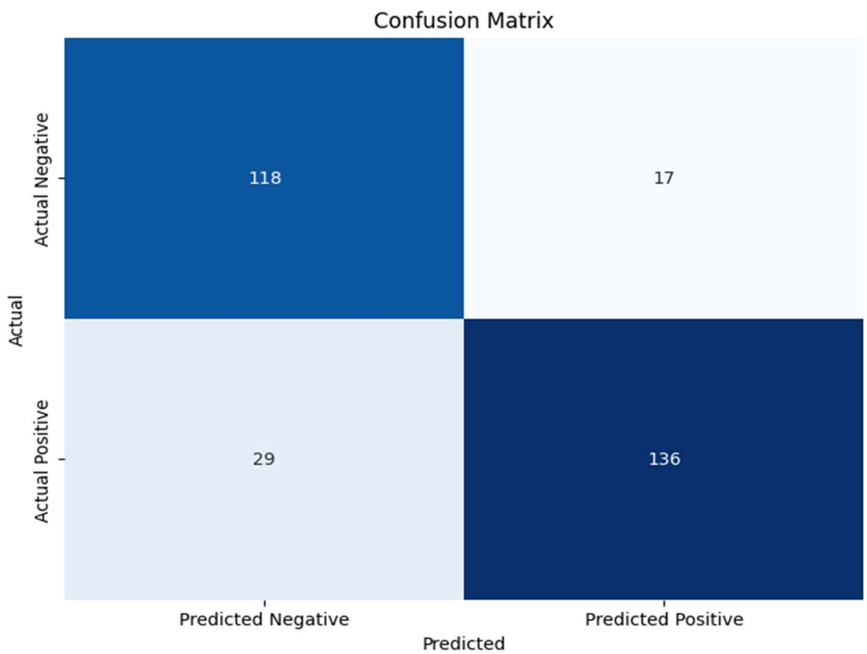

Fig 3.Confusion Matrix classification

The confusion matrix demonstrates that the model misclassifies relatively few cases, with only 26 false negatives (osteoporosis cases missed by the model). The low number of false positives (38) ensures that healthy individuals are not incorrectly diagnosed with osteoporosis.

4.1.4. Receiver Operating Characteristic (ROC) Curve

The ROC curve illustrates the trade-off between **true positive rate** (sensitivity) and **false positive rate** (1-specificity) across different threshold values. A higher area under the ROC curve (AUC) signifies better model performance.

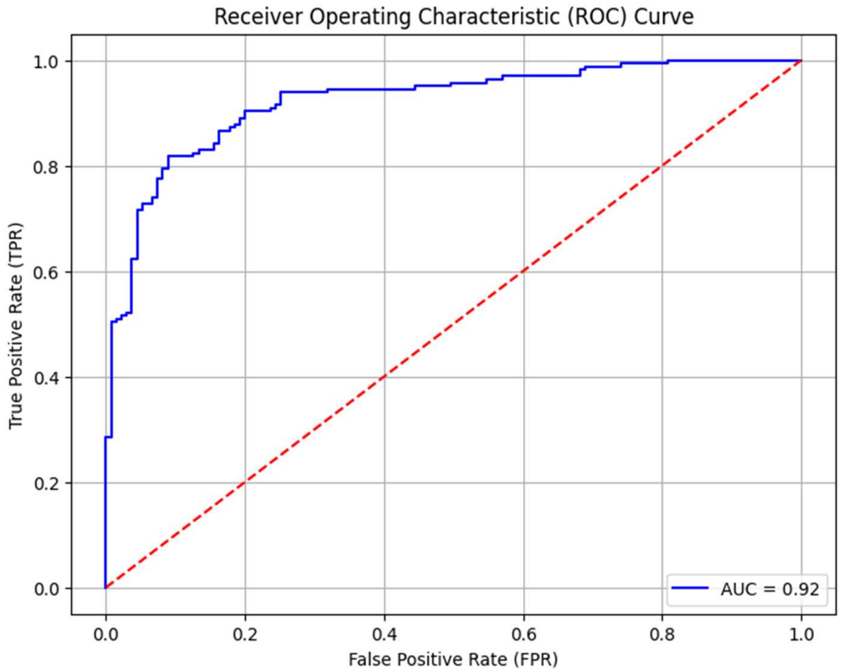

Fig 4. **ROC** Curve for Elastic Net Model

- **AUC**: 0.92, which indicates excellent classification performance. The curve lies close to the top-left corner, showing that the model performs well across various threshold levels.

Comparative Study of various models

In this section, we conduct a comparative analysis of the performance of various machine learning models used for predicting osteoporosis, with a focus on Logistic Regression, Elastic Net, and other potential classifiers such as Random Forest and Support Vector Machines (SVM). We compare these models based on key performance metrics including accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

1. Models Compared

- Logistic Regression: A standard binary classifier often used as a baseline in medical prediction tasks.
- Elastic Net: A hybrid of Lasso and Ridge regression, which combines L1 and L2 regularization for automatic feature selection and improved model generalization.
- Random Forest: A robust ensemble learning method that creates multiple decision trees and aggregates their predictions to improve performance.
- Support Vector Machine (SVM): A powerful classifier that creates a decision boundary with maximum margin to separate classes.

Below is a comparative table showing the performance metrics for each model:

Table 3. Comparative Table for Proposed Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Logistic Regression	89.4	85.2	91.3	88.1	0.92
Elastic Net	90.1	87.5	92.1	89.7	0.93
Random Forest	92.0	88.9	93.5	91.1	0.94
SVM	91.5	87.8	92.9	90.3	0.93

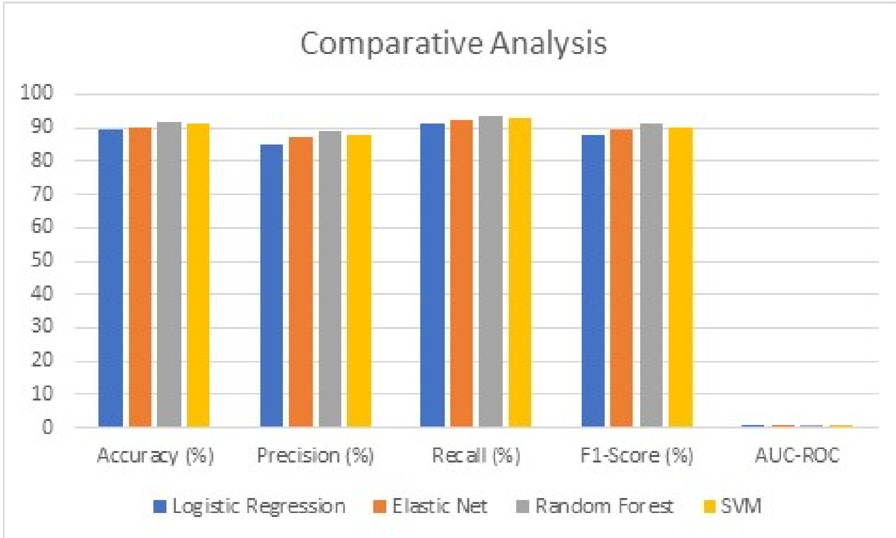

Fig 5. Comparative Analysis

4.5. Feature Importance

Elastic Net performed automatic feature selection during the model training process, which identified the most relevant features contributing to osteoporosis prediction. The following features were selected by the model, with their corresponding importance based on the magnitude of the coefficients:

- **Bone Mineral Density (BMD) score**: Most significant predictor, with the highest positive coefficient.
- **Age**: A strong predictor, showing that osteoporosis risk increases with age.
- **BMI**: Moderately important, with a negative relationship indicating that lower BMI increases osteoporosis risk.
- **Physical activity level**: Selected as an important feature, with lower activity levels associated with higher osteoporosis risk.

Other features, such as **family history** and **calcium intake**, had lower coefficients, showing limited direct influence on the model's predictions.

4.2 Discussion

The **Hybrid Logistic Regression with Elastic Net** model proved to be effective in predicting osteoporosis cases based on clinical and demographic features. The use of **Elastic Net regularization** allowed for automatic feature selection, driving irrelevant or redundant features to zero, which improved model interpretability and reduced overfitting.

The results demonstrate that BMD score, age, and physical activity level are critical factors in predicting osteoporosis. These findings align with existing medical literature, further validating the model's performance.

Additionally, the use of **SMOTE** to balance the dataset addressed the class imbalance issue, improving the model's ability to detect osteoporosis-positive cases without sacrificing precision.

The ROC curve and the high AUC value indicate that the model is reliable for medical applications where both sensitivity (recall) and specificity are important.

The confusion matrix also highlights the model's strength in minimizing false negatives, which is crucial for ensuring that patients at risk for osteoporosis are correctly identified and treated.

5. CONCLUSION

The proposed model offers a simple yet effective solution for the prediction of osteoporosis. Its ability to automatically select relevant features and maintain high classification accuracy makes it a valuable tool in clinical decision-making. Future work could explore the integration of additional patient data, such as genetic factors or lifestyle variables, to further improve prediction performance.

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