



Research Article

Comparative Machine Learning Models for Dementia Prediction Using SMOTE

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Abstract:

Dementia is a progressive neurodegenerative disorder that leads to cognitive decline and significantly affects patients' quality of life. Early detection is crucial for determining appropriate medical interventions and slowing disease progression. This study aims to develop a machine learning-based dementia prediction model and compare the performance of three algorithms: Support Vector Machine (SVM), Random Forest (RF), and XGBoost. The dataset, obtained from the Kaggle platform, consists of 373 MRI-based patient records categorized into three diagnosis groups: Converted, Demented, and Nondemented. To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied. Experimental results show that the XGBoost algorithm achieved the best performance, with an accuracy of 93.86%, precision of 94%, recall of 94%, and F1-score of 94%, outperforming SVM and Random Forest. The application of SMOTE improved the model's sensitivity to minority classes. The combination of XGBoost and SMOTE demonstrates high accuracy in dementia prediction and holds potential for integration into clinical decision support systems (CDSS) to assist early diagnosis.

Keywords: Dementia Prediction, SMOTE, XGBoost, Random Forest, SVM, CDSS

Dataset link: -

1. Introduction:

Dementia is a progressive neurodegenerative disorder characterized by a decline in cognitive functions, significantly impacting patients' quality of life and imposing substantial socioeconomic burdens worldwide [1]. According to the World Health Organization (WHO, 2023), more than 55 million people currently live with dementia, and this number is expected to double by 2050 [2]. Early detection of dementia is crucial to enabling timely medical intervention and slowing disease progression. However, conventional diagnostic approaches still rely heavily on clinical assessment and neuroimaging, which are both time-consuming and costly, making large-scale early screening impractical.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new opportunities for data-driven medical diagnostics. Numerous studies have proposed predictive models to identify dementia risk using demographic, neuropsychological, and clinical data. Research [3] utilized a Support Vector Machine classifier to predict dementia severity based on cognitive assessment scores, demonstrating the feasibility of ML in dementia classification implemented a Random Forest model to predict the transition from mild cognitive impairment (MCI) to

dementia, achieving an accuracy of 88%. Furthermore, [4] showed that Extreme Gradient Boosting (XGBoost) can effectively handle non-linear clinical data, yielding diagnostic accuracy above 93%.

Despite these promising results, previous studies exhibit several limitations. First, most existing models are trained on imbalanced datasets, where non-demented cases dominate early or converted dementia classes. This imbalance biases the models toward the majority class, thereby reducing sensitivity to minority cases and leading to misleading performance metrics. Second, comparative evaluations across multiple ML algorithms under controlled experimental settings are limited, as many studies focus on a single model, making it difficult to determine the optimal algorithm for dementia prediction. Third, few studies explicitly integrate data balancing techniques such as SMOTE into dementia prediction frameworks, which limits their applicability in real-world clinical datasets that inherently suffer from imbalance.

To address these gaps, this study proposes a comprehensive machine learning framework for dementia prediction that integrates the Synthetic Minority Oversampling Technique (SMOTE) to mitigate data imbalance, followed by a comparative evaluation of three widely used algorithms Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). By systematically comparing these models on a balanced dataset, the research aims to identify the algorithm that offers the best trade-off between accuracy and sensitivity to minority classes.

The main objectives of this study are to:

1. Evaluate and compare the predictive performance of RF, SVM, and XGBoost in multi-class dementia classification.
2. Assess the effect of applying SMOTE on model performance, particularly in enhancing detection for minority classes.
3. Identify the most robust model that can potentially be integrated into a Clinical Decision Support System (CDSS) for early dementia detection.

The novelty of this study lies in combining SMOTE-based data balancing with a comprehensive comparative evaluation of multiple ML algorithms using the same dataset, providing an empirical understanding of their performance under balanced conditions. The findings are expected to contribute to the development of reliable, data-driven decision support tools in neuroinformatics and early dementia diagnosis.

In summary, this research contributes both theoretically and practically to the field of neuroinformatics and predictive healthcare. It not only enriches the existing literature on ML-based dementia prediction but also provides a methodological framework that can be adapted for broader clinical applications in early disease detection.

2. Method:

This research was conducted through several stages to obtain an optimal dementia prediction model. In general, the research stages include: dataset collection, data pre-processing, class distribution balancing, machine learning model training and testing, and model performance evaluation. **Figure 1** shows the research flow.

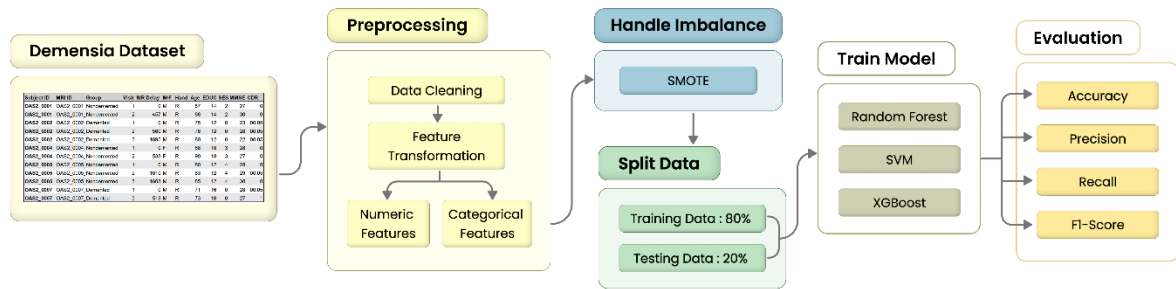


Figure 1. Research Flow

a. Dataset

The dataset used was obtained from the Kaggle platform, containing clinical and demographic data of patients across three diagnostic categories Converted, Demented, and Nondemented [5]. The data was then processed and used to train a machine learning model to classify the level of dementia based on available features.

b. Preprocessing Data

The pre-processing stage is performed to ensure the data is ready for use in the model training process. This stage includes:

- Data Cleaning

At this stage, we check for missing values, outliers, and data inconsistencies. Missing values are filled in using the imputation method using the mean or mode, depending on the variable type [6].

- Feature Transformation

All numeric features are normalized to equalize the scale between variables, so that no single feature dominates the model learning process. For categorical features, an encoding process is performed using the Label Encoding technique so that they can be processed by the machine learning algorithm [7].

c. Handle Imbalance Data Using SMOTE

The dementia dataset is characterized by class imbalance because the amount of data in the Nondemented category is significantly greater than the Converted and Demented categories. This condition can lead to model bias, where the model tends to classify data into the majority class. To address this issue, the Synthetic Minority Oversampling Technique (SMOTE) method was applied. SMOTE works by generating new synthetic samples for the minority class based on interpolation between existing samples [8]. This technique not only increases the data volume but also enriches the minority data distribution without significantly adding noise. The application of SMOTE is expected to improve the model's ability to recognize patterns in

the minority class, resulting in more balanced classification results [9]. To illustrate the effect of the SMOTE method on class distribution, **Figure 2** visualizes the data before and after the balancing process.

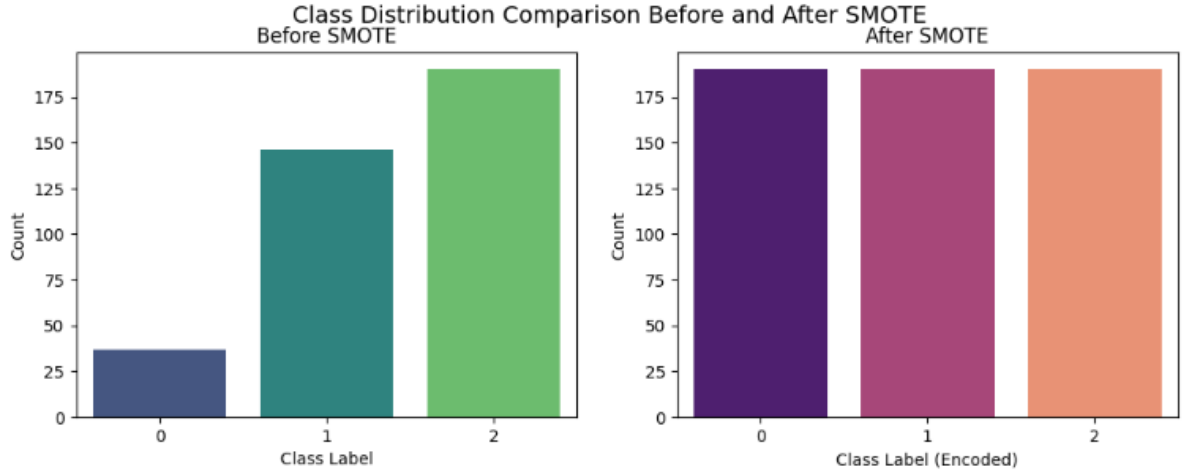


Figure 2. Class distribution before and after the implementation of SMOTE

d. Split Data

After preprocessing and balancing, the dataset was divided into training and testing subsets with a ratio of 80:20 using stratified sampling to maintain class proportions. All experiments were conducted using Python 3.10, with implementations based on open-source libraries including Scikit-learn, XGBoost, NumPy, and Pandas.

e. Algorithms

This study uses three different machine learning algorithms to compare their performance, namely Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost).

- SVM

The SVM algorithm works by finding the optimal hyperplane that separates data classes with the maximum margin [10], [11]. The main goal of SVM is to minimize classification error by maximizing the distance between the separating hyperplane and the nearest data point from each class [12], [13]. Because the data is nonlinear, a Radial Basis Function (RBF) kernel is used to map the data to a higher-dimensional space. Mathematically, the SVM optimization function can be expressed as equation (1).

$$\min_{w,b,\xi} \frac{1}{2}|w|^2 + C \sum_{i=1}^n \xi_i \quad (1)$$

with limitations (2):

$$y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad (2)$$

w represents the weight vector that determines the orientation of the separating plane (hyperplane) in the feature space, while b is the bias that adjusts the plane's position relative to the origin. The value of ξ_i is called the slack variable, a tolerance variable used to accommodate data that cannot be perfectly separated by a hyperplane. The parameter C is a regularization constant that controls the trade-off between the maximum margin and the classification error in the training data; the larger the C value, the lower the tolerance for classification error. Furthermore, the function $\phi(x)$ is a nonlinear mapping function that transforms data from a low-dimensional space to a higher-dimensional space, so that data that was originally linearly inseparable can be separated with a more optimal margin.

The RBF kernel used is defined as (3):

$$K(x_i, x_j) = \exp(-\gamma|x_i - x_j|^2) \quad (3)$$

This approach allows SVM to handle non-linearly separable data distributions, as well as improving the model's ability to detect complex patterns between features in the case of multi-class dementia classification.

- Random Forest

Random Forest is an ensemble learning-based algorithm that combines multiple decision trees to produce more accurate and stable predictions [14], [15]. Each tree is built based on a randomly selected subset of data and features [16], [17]. The final prediction is obtained through a majority voting process for classification or averaging for regression, which can be mathematically written as equation (4).

$$\hat{y} = \text{mode}(h_1(x), h_2(x), \dots, h_K(x)) \quad (4)$$

$h_t(x)$ indicates the classification outcome of the t -th tree, while K represents the overall number of trees in the model. The function {mode} chooses the class label that appears most often as the prediction. Random Forest was chosen for this study because it can handle high-dimensional features efficiently, is stable against noise, and provides competitive classification results across different data types.

- XGBoost

XGBoost is a gradient boosting-based algorithm that builds a predictive model incrementally. Each new tree is added to correct the prediction errors made by the previous model [18], [19]. This process is based on the principle of additive learning, where the final model is the sum of a number of weak learners [20]. In general, the objective function of XGBoost can be expressed as (5).

$$\mathcal{L}(\phi) = \sum_{i=1}^n l(y_i, \widehat{y}_i^{(t)}) + \sum_{k=1}^t \Omega(f_k) \quad (5)$$

Where $l(y_i, \widehat{y}_i^{(t)})$ is the loss function between the actual labels y_i and prediction $\widehat{y}_i^{(t)}$. $\Omega(f_k)$ is a regularization function that controls the complexity of the k^{th} tree, and f_k is the decision function of the k^{t} tree.

The predictions are updated iteratively as equation (6):

$$\widehat{y}_i^{(t)} = \widehat{y}_i^{(t-1)} + \eta f_t(x_i) \quad (6)$$

η is learning rate controls the contribution of each new tree to the overall model. This approach makes XGBoost superior in handling high-dimensional data, reducing overfitting through L1 and L2 regularization, and increasing computational efficiency by parallelizing the training process.

f. Evaluation

All three models were trained using SMOTE balanced data, with a ratio of 80% training data and 20% test data. Parameter optimization was performed using a grid search approach to obtain the best parameter combination that yields maximum performance. Four evaluation metrics are used in this study, namely accuracy, precision, recall, and F1-score, each of which is calculated based on the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. Equations (7) - (10) explain how to calculate F1-score, recall, accuracy, and precision.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

TP refers to the condition when the model correctly classifies the sample as positive. Meanwhile, TN occurs when the model correctly identifies the sample as a negative class. Conversely, FP occurs when the model erroneously classifies a negative sample as positive, and FN refers to the condition when the model fails to detect a sample that actually belongs to the positive class.

3. Result and Discussion:

Result

Experimental results showed significant differences in the performance of the three machine learning algorithms used to predict dementia levels: Converted, Demented, and Nondemented. The evaluation used four key metrics: accuracy, precision, recall, and F1-score, to obtain a comprehensive overview of the model's performance.

Table 1. Evaluation Results of Machine Learning Models for Dementia Prediction

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 – Score (%)
Random Forest	91.23	91.00	91.00	91.00
SVM	82.46	84.00	82.00	83.00
XGBoost	93.86	94.00	94.00	94.00

Based on the results in Table 1, The XGBoost algorithm achieved the highest performance, with an accuracy of 93.86%, precision of 94%, recall of 94%, and F1-score of 94%. This superior performance highlights XGBoost’s capability to handle complex, nonlinear interactions between features, attributed to its gradient boosting mechanism that iteratively corrects residual errors from prior trees. Random Forest, although achieving a slightly lower accuracy (91.23%), still demonstrated strong performance due to its ensemble bagging approach, which mitigates overfitting and provides robust generalization. Meanwhile, SVM achieved the lowest performance (82.46%), reflecting its sensitivity to nonlinear feature distributions and its limited adaptability to high-dimensional, imbalanced medical datasets.

To gain a more detailed understanding of each model's classification capabilities, we analyzed the confusion matrix of the best-performing model, XGBoost. [Figure 3](#) displays the confusion matrix of the XGBoost prediction results on the test data.

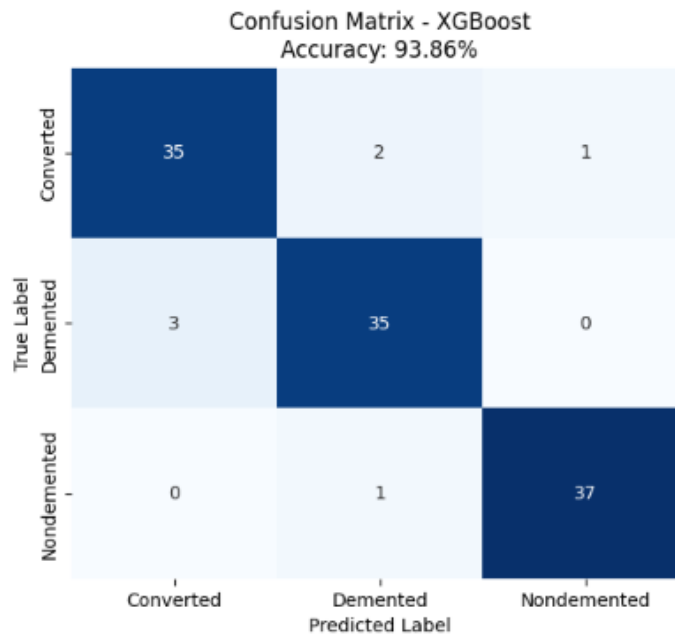


Figure 3. Confusion Matrix Model XGBoost in Dementia Prediction

The confusion matrix shows that the XGBoost model has a high correct classification rate across all classes, especially the Nondemented category, which has the largest amount of data. Some misclassifications still occur in the

Converted class, which is sometimes predicted as Demented, which can be explained by the similarity in clinical features between the two conditions. However, overall, the model maintains a balanced performance across classes with nearly uniform recall rates, indicating the effectiveness of the SMOTE technique in addressing data imbalance.

This analysis reinforces the finding that XGBoost is the most effective algorithm for detecting dementia, with a combination of high accuracy, precision, and generalizability. This improved performance demonstrates that boosting-based models are capable of capturing the complex nonlinear patterns often found in medical and psychometric data of dementia patients.

Discussion

The results of this study provide empirical evidence that the application of boosting-based machine learning algorithms, specifically XGBoost, has strategic potential in supporting the early detection of dementia. With an accuracy of over 93%, this model can serve as an analytical tool to identify patients at risk of cognitive decline at an early stage. This advantage can be integrated into a Clinical Decision Support System (CDSS) to assist healthcare professionals in objective, data-driven patient screening. Implementing an XGBoost-based system has the potential to improve diagnostic accuracy, accelerate the identification process, and reduce reliance on costly neuroimaging examinations.

From a healthcare efficiency perspective, the application of machine learning-based predictive models allows for rapid and automated classification without compromising the reliability of the results. With stable performance across all evaluation metrics, this model can support more efficient clinical decision-making, particularly in environments with limited expertise or advanced diagnostic facilities. The use of predictive models like XGBoost can also assist healthcare professionals in prioritizing interventions for patients showing early signs of dementia, allowing for more effective allocation of care resources.

Furthermore, the results of this study have implications for the development of preventative and personalized healthcare systems. The integration of machine learning models into longitudinal patient data monitoring enables the continuous identification of cognitive changes, which can ultimately support early intervention strategies and predictive care. Thus, utilizing machine learning for dementia prediction contributes not only to improved diagnostic accuracy but also to care efficiency, reduced economic burden, and improved overall quality of life for patients.

4. Conclusion:

This study presented a comparative evaluation of three machine learning algorithms SVM, RF, and XGBoost for the classification of dementia conditions, including *Converted*, *Demented*, and *Nondemented* categories. Using a dementia dataset obtained from Kaggle, the research implemented the Synthetic Minority Oversampling Technique (SMOTE) to address the issue of class imbalance commonly found in medical data. The experimental findings demonstrated that XGBoost achieved the highest predictive performance, with an accuracy of 93.86%, precision of 94%, recall of 94%, and an F1-score of 94%, outperforming both Random Forest and SVM. These results indicate that the boosting-based learning mechanism of XGBoost effectively captures complex, non-linear feature interactions and provides robust classification outcomes even in the presence of imbalanced data distributions.

The application of SMOTE proved effective in enhancing model sensitivity toward minority classes, particularly *Converted* and *Demented*, thereby reducing bias toward the majority class (*Nondemented*). The consistency of the

evaluation metrics across all models further suggests that machine learning approaches, especially ensemble-based algorithms like XGBoost, have strong potential to be implemented in Clinical Decision Support Systems (CDSS) for early dementia detection. Such systems could assist healthcare professionals by providing faster, data-driven diagnostic insights that contribute to more accurate clinical decision-making, improved patient management, and efficient resource allocation in healthcare institutions.

Nevertheless, this study has several limitations that should be acknowledged. The dataset used in this research was limited in both size and diversity, with a relatively small number of *Converted* and *Demented* cases, which may constrain the model's generalizability to broader clinical populations. Moreover, the dataset primarily consisted of tabular clinical attributes without incorporating additional modalities such as neuroimaging, genetic, or behavioral data, which could potentially enrich the predictive capacity of the model. Another limitation lies in the use of a single data split (80:20) for training and testing, without cross-validation, which may introduce variability in performance estimation and reduce robustness. These constraints indicate that while the proposed approach shows strong potential, further validation with larger, heterogeneous, and multi-source datasets is necessary to confirm the reliability of the findings.

Future studies are encouraged to expand the current research in several directions. Integrating multimodal data sources such as neuroimaging, genetic markers, and cognitive test results could substantially enhance model accuracy and interpretability. In addition, the incorporation of explainable AI (XAI) methods, such as SHAP or LIME, would allow for better understanding of feature contributions to model predictions, improving clinical transparency and trust. Exploring advanced hybrid architectures that combine ensemble methods and deep learning—such as XGBoost-CNN or Deep Forest—may also yield further improvements in performance. Furthermore, employing *k*-fold cross-validation and external validation using independent datasets is recommended to strengthen the generalization and clinical applicability of the model.

In conclusion, this research provides empirical evidence that machine learning, particularly ensemble-based methods such as XGBoost coupled with SMOTE balancing, can serve as an effective framework for early dementia prediction. The proposed approach not only enhances classification accuracy and sensitivity toward minority dementia classes but also establishes a methodological foundation for developing intelligent, data-driven systems to support early detection, timely intervention, and improved healthcare efficiency in neurodegenerative disease management.

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