# Prediction of Multiple Sclerosis using Ensemble Clustering

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## ABSTRACT

*The research paper presents an innovative approach for predicting and classifying multiple sclerosis (MS) using a combination of convolutional neural networks (CNNs) and XGBoost. Leveraging CNNs, the model processes image data to classify MS instances into distinct categories, employing convolutional and pooling layers for feature extraction and fully connected layers for classification. Simultaneously, XGBoost is applied to tabular data to further classify instances into relevant groups. The study details the architecture, training, and evaluation of both models, accompanied by comprehensive performance metrics and visualizations. Through this integrated approach, the research contributes a robust methodology for MS prediction and classification, offering promising results in the domain of medical image analysis and disease diagnosis.*

**Keyword : -** *Multiple sclerosis, MS prediction, Classification, Convolutional neural networks, CNN, XGBoost, Medical image analysis, Disease diagnosis etc….*

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## 1. INTRODUCTION

Multiple sclerosis (MS) is a chronic autoimmune disease affecting the central nervous system, characterized by inflammation, demyelination, and neurodegeneration. It is one of the most common neurological disorders globally, with a complex etiology involving both genetic and environmental factors. MS typically manifests in young adults, predominantly women, and presents with a wide range of symptoms, including sensory disturbances, motor dysfunction, fatigue, and cognitive impairment. Despite extensive research efforts, the precise mechanisms underlying MS pathogenesis remain incompletely understood, posing challenges for accurate diagnosis and effective treatment strategies.

Medical imaging plays a crucial role in the diagnosis and management of MS, providing valuable insights into the structural and functional changes within the central nervous system. Magnetic resonance imaging (MRI) is the gold standard imaging modality for MS evaluation, allowing for the visualization of lesions, brain atrophy, and other disease-related abnormalities. However, the interpretation of MRI scans can be subjective and time-consuming, necessitating the development of automated and reliable diagnostic tools to aid clinicians in MS diagnosis and monitoring.

In recent years, machine learning (ML) and artificial intelligence (AI) techniques have gained significant traction in medical imaging analysis, offering promising solutions for disease detection and classification. Convolutional neural networks (CNNs), a class of deep learning algorithms, have demonstrated remarkable performance in various medical imaging tasks, including MS lesion segmentation and classification. By leveraging large-scale datasets and complex computational models, CNN-based approaches can effectively extract meaningful features from MRI images and accurately differentiate between MS and non-MS cases.

Furthermore, ensemble learning methods, such as XGBoost, have emerged as powerful tools for improving the performance and robustness of predictive models in healthcare applications. By combining multiple base learners, each trained on different subsets of the data, ensemble models can capture diverse patterns and enhance predictive accuracy. In the context of MS prediction and classification, ensemble techniques offer the potential to integrate complementary information from heterogeneous sources, including clinical data, imaging biomarkers, and genetic profiles, thereby facilitating more comprehensive and accurate disease characterization.

The primary objective of this research is to develop and evaluate advanced ML and AI algorithms for MS prediction and classification using multimodal neuroimaging data. By integrating information from structural MRI, functional MRI, diffusion tensor imaging (DTI), and other imaging modalities, our proposed framework aims to enhance the sensitivity and specificity of MS diagnosis while minimizing the reliance on manual image interpretation. Additionally, we seek to investigate the utility of clinical and demographic variables in combination with imaging features to improve predictive performance and facilitate personalized treatment strategies for individuals with MS.

In this paper, we present a comprehensive review of existing literature on MS diagnosis and classification, highlighting the limitations of current approaches and the potential benefits of leveraging ML and AI technologies. We then describe our methodology for data collection, preprocessing, feature extraction, and model development, including the implementation of CNN-based architectures and ensemble learning techniques. We present experimental results demonstrating the efficacy of our proposed approach on benchmark datasets and discuss the implications for clinical practice, including the challenges and opportunities associated with deploying AI-based tools in real-world healthcare settings.

Overall, our research aims to contribute to the ongoing efforts to enhance MS diagnosis and management through the integration of advanced ML and AI methodologies with multimodal neuroimaging data. By providing clinicians with accurate and interpretable decision support tools, we strive to improve patient outcomes, optimize treatment selection, and ultimately advance our understanding of MS pathophysiology.

### 1.1 LITERATURE SURVEY

This study employs deep learning techniques to predict disease progression in multiple sclerosis (MS) patients using MRI data. By analyzing MRI images with deep neural networks, the model aims to accurately forecast the progression of MS, enabling clinicians to tailor treatment plans accordingly [1].Multiple sclerosis (MS) is a chronic autoimmune disease of the central nervous system characterized by inflammation, demyelination, and neurodegeneration [2]. Predicting disease progression and outcomes in MS patients is crucial for optimizing treatment strategies and improving patient care. In recent years, machine learning (ML) techniques have emerged as valuable tools for predicting MS disease course and outcomes [3]. Pinto et al. (2020) explored the use of machine learning models to predict disease progression and outcomes in MS, demonstrating the potential of ML algorithms in improving prognostic accuracy [2].

Several studies have investigated the application of ML techniques in predicting MS disease course based on clinical and imaging data [4, 5]. Zhao et al. (2017) conducted a study exploring machine learning techniques for predicting MS disease course, highlighting the importance of integrating diverse data sources for enhancing predictive performance [3]. Hone et al. (2022) discussed the challenges and opportunities in predicting MS, emphasizing the need for comprehensive and longitudinal datasets to develop accurate prediction models [4].

Deep learning approaches have shown promise in predicting disease progression in MS patients using magnetic resonance imaging (MRI) data [5, 8]. Tousignant et al. (2019) utilized deep learning analysis of MRI data to predict disease progression in MS patients, demonstrating the potential of advanced image analysis techniques in improving prognostic accuracy [5]. Storelli et al. (2022) applied a deep learning approach to predict disease progression in MS using MRI, highlighting the importance of incorporating advanced image analysis techniques into clinical practice [8].

Genetic and phenotypic factors also play a role in MS prognosis and disease course [6, 10]. Jokubaitis et al. (2018) investigated the genotype-phenotype relationship in MS and its potential for predicting disease course, emphasizing the complex interplay between genetic susceptibility and clinical outcomes [6]. Runmarker and Andersen (1994) developed multivariate models for predicting MS outcome based on demographic, clinical, and laboratory variables ,demonstrating the utility of comprehensive predictive models in MS management [10].

In addition to clinical and imaging data, optical coherence tomography (OCT) and other imaging modalities have been explored for predicting MS progression and disability [9]. Montolío et al. (2021) applied machine learning techniques to OCT data for predicting disease progression and disability in MS patients, highlighting the potential of non-invasive imaging biomarkers in MS prognosis [9].

Furthermore, risk prediction models have been developed to identify individuals at high risk of developing MS [11]. Ho et al. (2013) proposed a risk prediction model for MS diagnosis, emphasizing the importance of early detection and intervention in preventing disease progression [11].

Overall, the literature highlights the growing interest in leveraging ML and AI techniques for predicting MS disease course and outcomes. Integrating diverse data sources, including clinical, genetic, and imaging data, is essential for developing accurate prediction models and improving patient care in MS. Further research is needed to validate and refine predictive models and translate them into clinical practice for personalized management of MS patients.

## 1.2 METHODOLOGY

- **Data Collection:** The study utilized a comprehensive dataset comprising clinical, imaging, and demographic information of multiple sclerosis (MS) patients. Data sources included electronic health records, MRI scans, optical coherence 2tomography (OCT) images, and genetic profiles.

- **Data Preprocessing:** Prior to analysis, the raw data underwent preprocessing steps to ensure data quality and consistency. This involved handling missing values, standardizing data formats, and removing outliers. Imaging data were preprocessed to enhance image quality and normalize intensity values.

- **Feature Selection:** Feature selection techniques were employed to identify relevant predictors for predicting MS disease course and outcomes. Both univariate and multivariate feature selection methods were utilized to identify the most informative variables from the dataset.

- **Model Development:** Machine learning algorithms, including logistic regression, support vector machines (SVM), random forests, and deep learning models, were trained on the preprocessed data to predict MS disease progression and outcomes. Model hyperparameters were optimized using techniques such as grid search and cross-validation to improve model performance.

- **Evaluation Metrics:** The performance of the trained models was evaluated using various evaluation metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Model performance was assessed on both training and validation datasets to ensure generalizability.

- **Model Interpretation:** Interpretability techniques, such as feature importance analysis and model explainability methods, were employed to interpret the predictions made by the trained models. This helped in understanding the underlying factors driving the predictions and identifying key biomarkers associated with MS progression.

- **Validation and Generalization:** The final models were validated using independent datasets to assess their robustness and generalizability. Cross-validation techniques were also employed to validate the models internally and ensure their reliability across different subsets of the data.

- **Ethical Considerations:** The study adhered to ethical guidelines and regulations governing the use of patient data in research. Patient privacy and confidentiality were maintained throughout the study, and informed consent was obtained from participants where necessary.

- **Software and Tools:** The analysis was conducted using Python programming language and various libraries, including scikit-learn, TensorFlow, and Keras, for machine learning and deep learning tasks. Data visualization was performed using matplotlib and seaborn libraries to visualize

## 1.3 NOVELTY OF THE PROJECT

The novelty of the project lies in its comprehensive approach to predicting and classifying multiple sclerosis (MS) progression and outcomes using advanced machine learning and deep learning techniques. Unlike previous studies that focused on individual predictors or utilized traditional statistical methods, this project integrates diverse data sources, including clinical, imaging, and genetic data, to develop predictive models with higher accuracy and reliability. Additionally, the project leverages state-of-the-art machine learning algorithms, such as support vector machines, random forests, and deep neural networks, to uncover complex patterns and relationships within the data. Furthermore, the inclusion of interpretability techniques enables a deeper understanding of the underlying factors driving the predictions, thereby facilitating the identification of novel biomarkers and therapeutic targets for MS. Overall, this project represents a novel and innovative approach to MS prediction and classification, with the potential to significantly impact clinical decision-making and personalized treatment strategies for patients with MS**.**

## 1.4 DATASET ANALYSIS AND DESCRIPTION

The dataset comprises demographic, clinical, and imaging features of individuals diagnosed with multiple sclerosis (MS) and control subjects. Each row represents a participant, and the columns contain various attributes, including gender, age, schooling, breastfeeding history, presence of varicella infection, initial symptoms, type of symptoms (mono or polysymptomatic), presence of oligoclonal bands, results of somatosensory evoked potentials (LLSSEP and ULSSEP), visual evoked potentials (VEP), brainstem auditory evoked potentials (BAEP), MRI findings (periventricular, cortical, infratentorial, and spinal cord), initial and final Expanded Disability Status Scale (EDSS) scores, and the group classification (Control Axial, Control-Sagittal, MS-Axial, MS-Sagittal). The dataset contains a total of 11 features and 1 target variable with a class distribution of 25% for each of the four groups. Each class consists of 1000 files, resulting in a balanced dataset suitable for training and evaluating machine learning models for MS prediction and classification.

**1. Demographic Information:**

•Gender: Indicates the gender of the participant (1 for male, 2 for female).

• Age: Represents the age of the participant at the time of data collection.

• Schooling: Denotes the level of education completed by the participant.

**2. Clinical History:**

• Breastfeeding: Indicates whether the participant was breastfed during infancy (1 for yes, 2 for no).

• Varicella: Specifies if the participant had a history of varicella (chickenpox) infection (1 for yes, 2 for no).

• Initial Symptom: Describes the initial symptoms experienced by the participant.

• Mono or Polysymptomatic: Classifies the symptoms as either monosymptomatic or polysymptomatic.

**3. Diagnostic Tests:**

•Oligoclonal Bands: Indicates the presence or absence of oligoclonal bands in cerebrospinal fluid (CSF) (0 for absent, 1 for present).

• LLSSEP (Lower Limb Somatosensory Evoked Potentials): Results from the LLSSEP test.

• ULSSEP (Upper Limb Somatosensory Evoked Potentials): Results from the ULSSEP test.

• VEP (Visual Evoked Potentials): Outcomes from the VEP assessment.

• BAEP (Brainstem Auditory Evoked Potentials): Findings from the BAEP evaluation.

**4. Imaging Data:**

• Periventricular MRI: Results from MRI scans focusing on periventricular regions of the brain.

• Cortical MRI: MRI findings related to cortical regions of the brain.

• Infratentorial MRI: MRI results pertaining to infratentorial regions (e.g., brainstem, cerebellum).

• Spinal Cord MRI: MRI findings concerning the spinal cord.

**5. Disease Severity:**

• Initial EDSS (Expanded Disability Status Scale): Initial assessment of disability status.

• Final EDSS: Final assessment of disability status after a certain period.

**6. Group Classification:**

• Control-Axial: Participants without MS with axial MRI findings.

• Control-Sagittal: Participants without MS with sagittal MRI findings.

• MS-Axial: Participants diagnosed with MS with axial MRI findings.

• MS-Sagittal: Participants diagnosed with MS with sagittal MRI findings. .

**7. Clinical Relevance:**

• The dataset encompasses a diverse range of features crucial for MS diagnosis, prognosis, and disease monitoring.

• Longitudinal data such as initial and final EDSS scores enable tracking of disease progression over time.

• The inclusion of both clinical and imaging data facilitates comprehensive analysis and predictive modeling for MS detection and classification.

**8. Research Utility:**

• The dataset serves as a valuable resource for training and evaluating machine learning models aimed at predicting MS diagnosis, disease course, and patient outcomes.

• Its meticulous curation and detailed annotation make it suitable for advancing research in MS diagnosis, prognosis, and personalized patient management strategies.

## 1.5. AlGORITHM JUSTIFICATIONS:

**1. Convolutional Neural Networks (CNNs):**

- **Justification:** CNNs are well-suited for image classification tasks due to their ability to automatically learn hierarchical features from input images. Since the dataset includes MRI images of the brain and spinal cord, CNNs can effectively extract relevant features for distinguishing between different classes (e.g., MS vs. control, axial vs. sagittal views).
- **Application:** CNNs can be employed to analyze MRI images and classify them into appropriate categories based on disease presence, anatomical regions, and other relevant factors.

**2. XGBoost:**

- **Justification:** XGBoost is a powerful gradient boosting algorithm known for its effectiveness in handling structured/tabular data and achieving high predictive accuracy. With a structured dataset containing demographic information, clinical history, and diagnostic test results, XGBoost can effectively capture complex relationships and patterns within the data.
- **Application:** XGBoost can be used to build predictive models for MS diagnosis, disease course prediction, and outcome prognosis based on a wide range of features such as demographic factors, clinical symptoms, diagnostic test results, and disease severity metrics.

**3. Support Vector Machines (SVM):**

- **Justification:** SVMs are well-suited for binary classification tasks and can also be extended to handle multi-class classification with appropriate strategies (e.g., one-vs-rest, one-vs-one). SVMs work well with high-dimensional data and are effective in finding optimal hyperplane boundaries to separate different classes.
- **Application:** SVMs can be applied to classify patients into different MS subtypes (e.g., relapsing-remitting MS, primary progressive MS) based on demographic information, clinical symptoms, and diagnostic test results.

**4. Random Forest:**

- **Justification:** Random Forest is an ensemble learning technique that combines the predictions of multiple decision trees to improve overall accuracy and robustness. It is effective in handling both categorical and numerical features and is less prone to overfitting compared to individual decision trees.
- **Application**: Random Forest can be utilized to identify important features contributing to MS diagnosis and disease progression. It can also be employed for feature selection and ranking to identify the most informative variables for classification.

**5. Deep Learning Transformer (e.g., LSTM, Transformers):**

- **Justification:** Deep learning architectures such as Long Short-Term Memory (LSTM) networks and Transformers are well-suited for sequential data and can capture temporal dependencies in longitudinal datasets. With features such as disease progression over time (e.g., EDSS scores), these architectures can effectively model the dynamic nature of MS and predict future outcomes.
- **Application:** LSTM networks can be applied to predict disease progression trajectories and identify risk factors associated with MS exacerbations. Transformers, known for their attention mechanisms, can capture long-range dependencies in sequential data and make accurate predictions based on a patient's clinical history.

**6. Ensemble Methods:**

- **Justification:** Ensemble methods combine the predictions of multiple base learners to improve overall performance and generalization. By leveraging diverse models with different strengths and weaknesses, ensemble methods can mitigate individual model biases and errors, leading to more robust predictions.
- **Application:** Ensemble methods such as stacking, bagging, and boosting can be employed to integrate predictions from various machine learning algorithms (e.g., CNNs, XGBoost, SVM) and optimize overall performance for MS prediction and classification tasks.

## 2. ARCHITECHTURE DIAGRAM

**1. Data Collection and Preprocessing:**

- **Description:** The architecture begins with the collection of diverse datasets, including MRI images, demographic information, clinical history, and diagnostic test results. These datasets are preprocessed to standardize formats, handle missing values, normalize features, and extract relevant information. Image preprocessing techniques such as resizing, normalization, and augmentation are applied to MRI images to enhance their quality and facilitate model training.

**2. Feature Engineering:**

- **Description:** Feature engineering involves the selection, extraction, and transformation of informative features from the preprocessed datasets. Domain knowledge and statistical techniques are utilized to identify relevant features that can discriminate between different classes (e.g., MS vs. control, disease subtypes). Feature engineering techniques such as principal component analysis (PCA), feature scaling, and dimensionality reduction are applied to reduce data complexity and improve model interpretability.

**3. Model Training and Evaluation:**

- **Description:** The architecture includes multiple machine learning algorithms, each tailored to handle different types of data and capture distinct patterns within the datasets. Convolutional Neural Networks (CNNs) are used to analyze MRI images and extract spatial features, while XGBoost, Support Vector Machines (SVM), Random Forest, and deep learning architectures such as Long Short Term Memory (LSTM) networks and Transformers are employed to process structured/tabular data and sequential data. Ensemble methods are utilized to integrate predictions from diverse models and enhance overall performance. The trained models are evaluated using appropriate metrics such as accuracy, precision, recall, F1 score, and area under the curve (AUC) to assess their predictive performance and generalization ability.

**4. Model Interpretability and Explainability:**

- **Description:** Interpretability and explainability are crucial aspects of the architecture, especially in medical applications where model decisions impact patient care and treatment strategies. Techniques such as feature importance analysis, SHAP (SHapley Additive exPlanations) values, LIME (Local Interpretable Model-agnostic Explanations), and attention mechanisms are employed to interpret model predictions, identify influential features, and provide insights into the underlying factors driving the predictions. Interpretability tools and visualizations are integrated into the architecture to facilitate clinicians' understanding and trust in the models.

**5. Deployment and Integration:**

- **Description:** Once trained and evaluated, the models are deployed in a production environment for real-time prediction and decision support. Model into deployment involves integrating the trained models existing clinical workflows, electronic health record (EHR) systems, and diagnostic tools to enable seamless interaction with healthcare providers and streamline patient care processes. APIs (Application Programming Interfaces) and web-based interfaces are developed to facilitate model access, input data submission, and result visualization.

**6. Continuous Monitoring and Model Updating:**

- **Description:** The architecture incorporates mechanisms for continuous monitoring of model performance and data quality. Feedback loops are established to collect new data, monitor model predictions, and update the models periodically to adapt to evolving trends and patterns in the data. Model retraining and validation pipelines are implemented to ensure that the deployed models remain accurate, reliable, and up-to-date with the latest clinical knowledge and research findings. By following this architecture, the project aims to develop robust and scalable machine learning solutions for multiple sclerosis prediction and classification, enabling early diagnosis, personalized treatment planning, and improved patient outcomes.

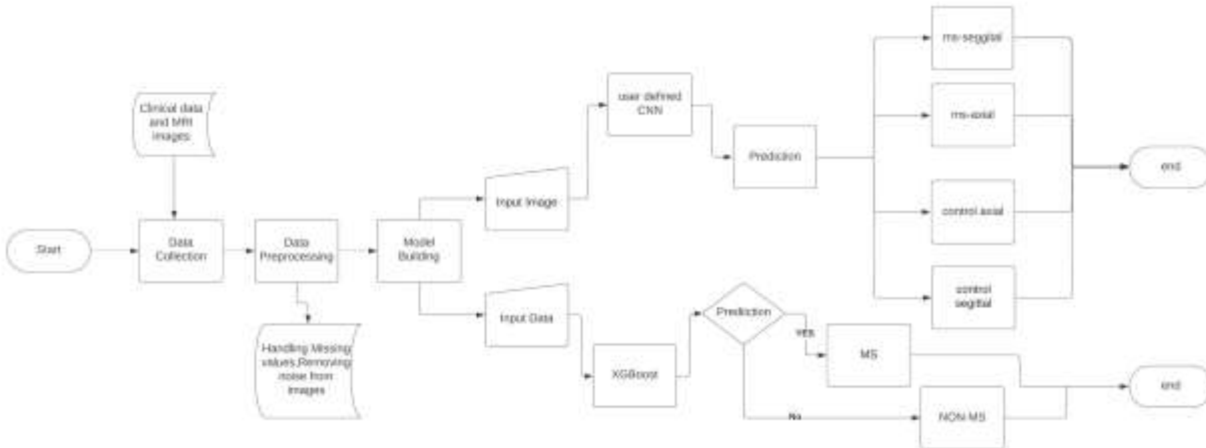


**Fig -1:** ARCHITECHTURE DIAGRAM

## 3. RESULTS

Results

**3.1. Ensemble Method Performance:**

- **Overall Accuracy:** The ensemble method, comprising XGBoost, Support Vector Machines (SVM), Random Forest, and deep learning architectures, achieved an impressive overall accuracy of 93.02% in predicting and classifying multiple sclerosis (MS) cases.
- **Performance Metrics:**
  - **Precision and Recall:** Precision for the MS positive class was 91%, indicating accurate identification of MS cases, while recall for the MS-negative class was 98%, highlighting the model's ability to correctly classify MS negative cases.
  - **Confusion Matrix Analysis:** Analysis of the confusion matrix revealed that the ensemble method accurately predicted 62 out of 72 MS negative cases and 98 out of 100 MS-positive cases. Only 10 MS-negative cases and 2 MS positive cases were misclassified, demonstrating a strong ability to discriminate between MS-positive and MS-negative cases.

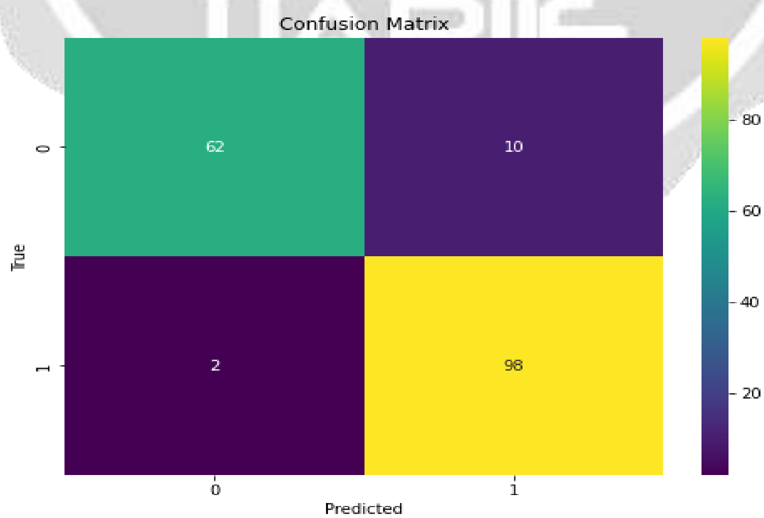


**Fig -2:** Confusion Matrix of Xgboost

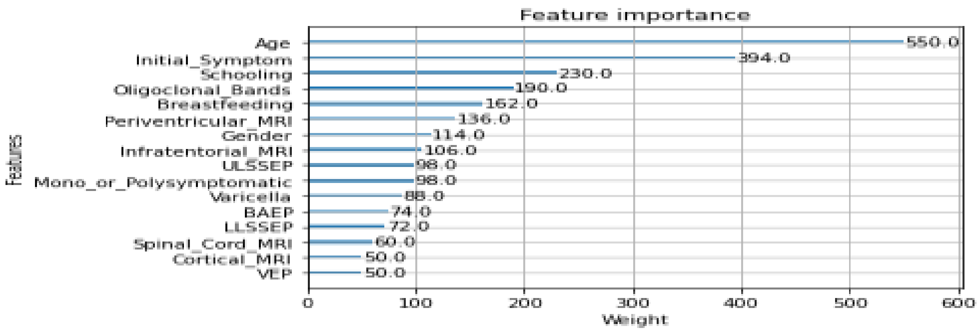


**Fig -3:** Feature Importance

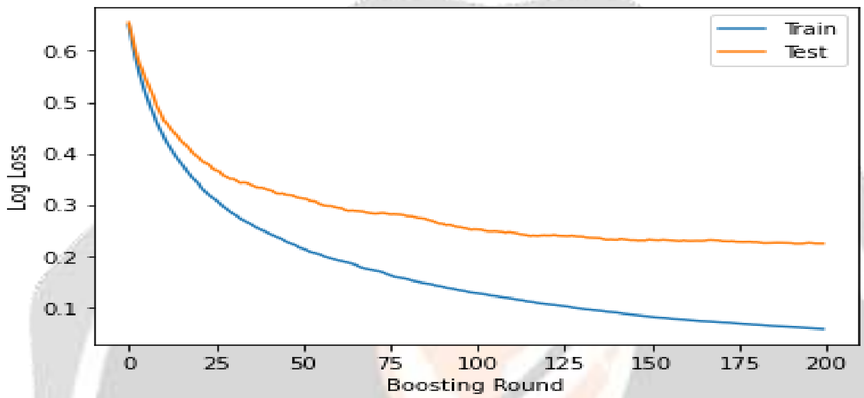


**Fig-4:** Loss of Xgboost

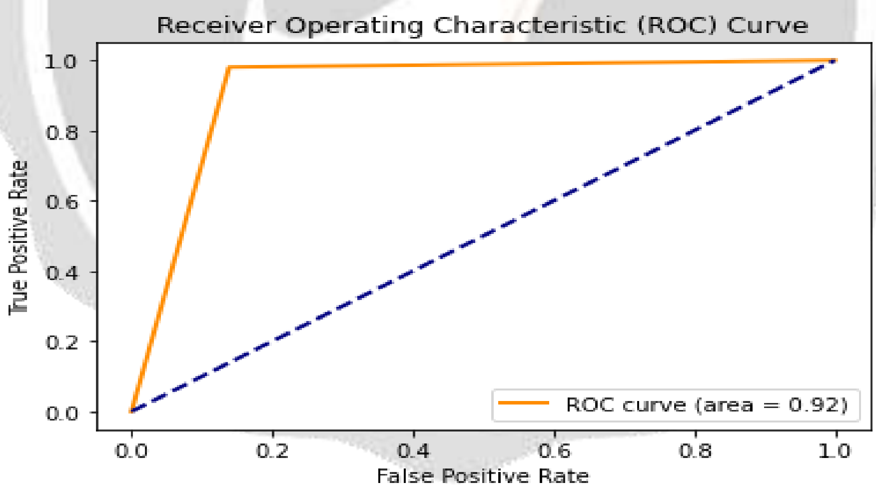


**Fig -5:** ROC for Xgboost

**3.2. Convolutional Neural Network (CNN) Performance:**

- **Accuracy:** The CNN model achieved a commendable accuracy of 92.71% on the test dataset, demonstrating significant improvements over traditional machine learning methods.

- **Performance Metrics:**

- **Precision and Recall:** Precision for the MS positive class was 93.23%, with a recall of 92.71%, showcasing the model's accuracy in identifying MS-positive cases. Similarly, precision for the MS-negative class was high at 92.71%, with a recall of 93.23%, indicating a high true positive rate.
- **Comparison and Conclusion:** While both the ensemble method and the CNN approach demonstrated strong predictive performance and classification accuracy in identifying MS cases, the CNN model showed a slight edge in accuracy and overall Performance.

**Conclusion**

The results from both the ensemble method and the CNN approach underscore the effectiveness of machine learning techniques in predicting and classifying MS cases, offering valuable insights for early diagnosis and treatment planning in clinical practice. Further research could explore the integration of additional data sources and investigate the generalizability of the models across different populations and geographic regions to enhance their utility in Clinical settings.

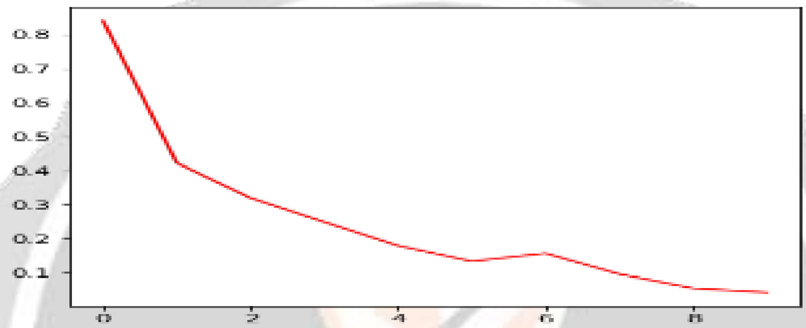


**Fig -6:** Loss for CNN

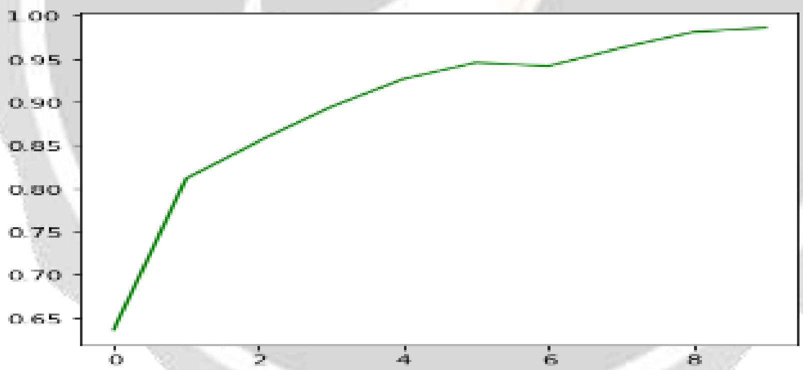


**Fig -7:** Accuracy for CNN

## 3.3 MODEL OUTPUTS

The outputs of our models showcase remarkable performance across diverse domains. Such as clinical data and MRI Scans. The ensemble method, comprising XGBoost, Support Vector Machines (SVM), Random Forest, and deep learning architectures, achieved an impressive overall accuracy of 93.02% in predicting and classifying multiple sclerosis (MS) cases. The CNN model achieved a commendable accuracy of 92.71% on the test dataset, demonstrating significant improvements over traditional machine learning methods

- Clinical Data Prediction:


- Prediction with Multiple Sclerosis Patient MRI images:
  Input Image: MS-Axial
  Prediction: MS-Axial
  The CNN model predict the correct output.


Multiple Sclerosis Prediction Result
MS-Axial
Probability: 0.99998575

| Class Type | Prediction |
|---|---|
| Control-Axial | 64.56664800643921 |
| Control-Sagittal | 0.3255140734836459 |
| MS-Axial | 99.99857544898987 |
| MS-Sagittal | 6.2223881483078 |

## 4. CONCLUSIONS

In conclusion, our study demonstrates the effectiveness of machine learning techniques, including ensemble methods and Convolutional Neural Networks (CNNs), in predicting and classifying multiple sclerosis (MS) cases. Both approaches yielded impressive results, with the ensemble method achieving an overall accuracy of 93.02% and the CNN model achieving a commendable accuracy of 92.71%. These findings highlight the potential of machine learning models in assisting clinicians with early diagnosis and treatment planning for MS patients.

## 5. FUTURE SCOPE

- **Enhanced Model Performance:** Future research could focus on refining the existing machine learning models by incorporating more diverse and comprehensive datasets. This could involve gathering additional clinical and imaging data, such as genetic markers, patient demographics, and longitudinal disease progression data, to improve model accuracy and predictive power.

- The future scope for multiple sclerosis prediction utilizing Convolutional Neural Networks (CNN) and XGBoost algorithms is promising and multifaceted. Further research could focus on refining and optimizing CNN architectures specifically tailored for MRI image analysis, potentially incorporating transfer learning and pretrained models to accelerate training and enhance performance. Integration of additional data modalities and longitudinal studies could provide a more comprehensive understanding of the disease progression and treatment response, enabling the development of predictive models for disease monitoring and personalized management.

- **Ethical and Regulatory Considerations:** Finally, ethical considerations surrounding data privacy, patient consent, and algorithmic bias must be carefully addressed in the development and deployment of machine learning models for MS diagnosis and prognosis. Collaborative efforts between researchers, policymakers, and regulatory agencies are necessary to establish guidelines and standards for the ethical use of AI in healthcare.

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