

Prediction of Multiple Sclerosis Using Neuro Detect-HDL: An Intelligent Diagnostic Framework

E.Kavi Priya¹,

Research Scholar & Assistant Professor, Department of CS with Cognitive systems and AIML,
Hindusthan College of arts & Science, Coimbatore

Dr.S. Sasikala²,

Professor and Head, Department of CS with Cognitive systems and AIML,
Hindusthan College of arts & Science, Coimbatore

Article History:

Received: 15-10-2025

Revised: 22-11-2025

Accepted: 10-12-2025

Abstract:

Multiple Sclerosis (MS) is a neurological disorder which affected the central nervous system that causes damages to the brain and the spinal cord. Mainly this disorder affects the immune system due to the damaged in a protective covering layer called as myelin sheath. The loss of myelin pigment causes inflammation in central nervous system (CNS) which affects the functionality of the brain. If the signal transmitted from the brain is affected, default it causes damages to the eye. There are certain traditional methods which is used to predict the accuracy rate. As this disorder causes serious issues, the fast prediction strategies should be applied for early diagnosis of MS. One of the methods uses meta-analysis which includes 41 ML/AI studies (5,989 individuals) were diagnosed in the year 2022 and predicted the accuracy rate up to 94%, sensitivity and specificity up to 92 to 93% and AUC up to 93%. Another method namely ensemble tree model uses clinical biomarkers such as age and blood test from Saudi Arabia in 2024 achieved 94.7% accuracy. Another traditional hybrid deep-learning model combining ML called as XGBoost produced the accuracy rate of 96.55%. In this research article, by using proposed method called as NeuroDetect-HDL (Neuro Disorder Detection via Hybrid Deep Learning) which produces the accuracy rate of 97%.

Keyword: Central Nervous System, Ensemble tree model, XGBoost, NeuroDetect-HDL

1. Introduction

Multiple Sclerosis is a chronic autoimmune disorder which causes the functionalities of the central nervous system (CNS) and leads to the damaged protective covering of a nervous system called as Myelin sheath. If the nervous fiber gets damaged, then the spinal cord and the brain routine work gets affected. Since a signal passing from the brain gets suck and the other parts of the body also get diffused. There are many reasons for the cause of MS. The some of the causes are mentioned below. Genetic factors which are not directly inherited but due to some family history there is a risk for increase. Environmental trigger is also a cause of MS which is due to

Low vitamin D level and limited sunlight exposure may increase MS risk. Viral infection such as Epstein-Barr virus (EBV) is a factor which causes disturbance in immune function. Smoking, Hormonal imbalance, Gut Microbiome and Autoimmune Response are also some of the factors which affects the functionality of CNS and causes MS [1].

The MS is characterized into four stages. The first stage is called as Clinically Isolated Syndrome (CIS). This stage leads to the single, first episode of neurologic symptoms lasting at least 24 hours. This stage may or may not develop into MS. The second stage is called as Relapsing-Remitting MS (RRMS) which leads clearly defined flare-ups (relapses) followed by periods of partial or complete recovery (remissions) and this is a common type (~85% of initial diagnoses). The third stage is called Secondary Progressive MS (SPMS) i.e., Initially begins as RRMS, then transitions to a steady worsening of symptoms over time, with or without relapses. The final stage is called as Primary Progressive MS (PPMS). In this stage, gradual worsening of neurologic function from the beginning, without early relapses or remissions and this stage is less common because it leads to final death.

The symptoms of MS are Fatigue, Numbness or tingling (often in the limbs), Muscle weakness or spasms, Difficulty walking or coordination problems, Vision problems (blurred or double vision, optic neuritis), Dizziness or vertigo, Bladder and bowel dysfunction, Cognitive issues (memory, attention problems) and Depression and emotional changes. As MS is a fast-spreading issues, an advanced techniques should be implemented for early prediction and diagnosing [2].

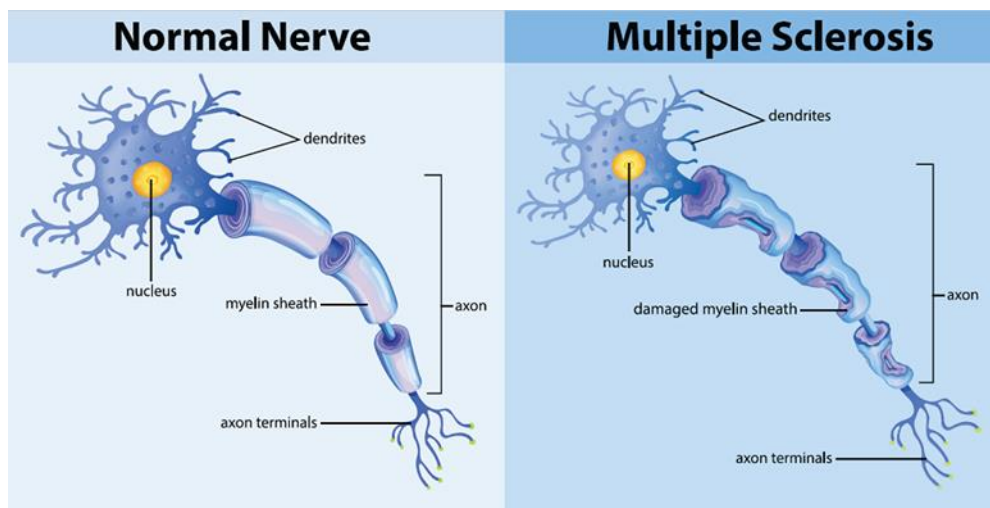


Fig: 1 Normal nervous system and MS affected nervous system

The traditional method for diagnosing MS includes Medical History and Neurological Examination which means analyzing patient's symptoms, medical history, and performs a physical and neurological exam. The next diagnosing method is Magnetic Resonance Imaging (MRI). Lumbar Puncture (Spinal Tap) is also a diagnosing method which involves removing and

analyzing a sample of cerebrospinal fluid (CSF), the fluid that surrounds the brain and spinal cord within the skull and backbone. Evoked Potentials Tests is a test which is classified into two types visual evoked potential (VEP) which measures the speed of nerve signals between eye and brain and somatosensory evoked potential (SSEP) which measures the speed of nerve signal between skin i.e., physical touch and brain. Blood Tests is also one of the diagnosing method and McDonald Criteria are the guidelines neurologists uses to diagnose MS. These methods predict the disease rate at less efficient. To enhance the predict rate the Machine learning (ML) and Deep learning (DL) techniques were implemented which efficiency is also too low. So, to enhance the prediction rate at the early stage the proposed technique called as NeuroDetect-HDL which achieves the accuracy rate up to 97%.

2. Literature review

Shoeibi et al. (2021) used deep learning for reviewing MS based on MRI which summarizes the prominent CAD systems. Xu et al. (2024) – Systematic review of 82 DL-MRI studies focused on lesion segmentation/classification. Zhang et al. (2023) – Multimodal neural network on EHR + imaging + clinical notes, improving AUROC by ~25% vs. uni-modal models.

Elhassan et al. (2022) used AI-Based Diagnostic Performance in MS: A Systematic Review and Meta-analysis focuses on Reviewed AI methods for MS diagnosis using imaging and clinical data and implemented technique CNN, SVM, Decision Trees found an accuracy ~94%.

Shoeibi et al. (2021) uses Applications of Deep Learning in Brain MRI for Multiple Sclerosis focuses on Survey of DL techniques for MRI segmentation, lesion detection, and classification implemented technique CNN, U-Net, ResNet for MS lesion detection and subtype classification.

Lorefice et al. (2022) uses Machine Learning Algorithms for Predicting Disability Progression in MS focuses on Predicting disability progression using ML models with clinical and MRI data and implemented technique Logistic Regression, Random Forest, XGBoost which produces accuracy 89%.

Abdulkadir et al. (2022) uses Artificial Intelligence for Predicting Multiple Sclerosis with Blood Biomarkers focuses ML model using blood-based biomarkers for MS prediction and implemented technique SVM, Decision Trees, Ensemble Models which produces accuracy 94.7%.

Roy et al. (2020) uses Deep Learning Approaches for MS Lesion Segmentation: Review focuses Systematic review of deep learning approaches for segmenting MS lesions in MRI and implemented technique U-Net, DeepMedic, V-Net.

Data Type	ML/DL Method	Task	Performance
Smartphone sensors	MLP + attention	Diagnosis	AUC = 0.88
Inertial gait data	CNN + transfer learning	Remote ambulation	Improved vs. SVM
MRI + DL	CNN, U-Net, attention frameworks	Segmentation/Detection	Up to ~96% accuracy
OCT + ML	Ensemble, LSTM	Diagnosis + prognosis	87.7% / 81.7%
EHR + Imaging	Multimodal DNN	Severity prediction	+25% AUROC
PROMs + MRI	Logistic, SVM, RF, NB	Progression forecast	~82–89% accuracy
Gait treadmill with IoT	GBM, MLP	Gait-based diagnosis	AUC up to 1.0

Table:1 Literature survey for MS

Moussavi et al. (2021) uses IoT-Enabled MS Diagnosis Using Wearable Sensor Data focuses on MS detection using wearable IoT devices for gait analysis and implemented technique SVM, ANN, KNN on motion sensor data.

Kogan et al. (2020) uses Smartphone-Based Digital Biomarkers for MS Diagnosis focuses on ML models using smartphone sensor data for MS detection and implemented technique MLP with attention, time-series deep learning and produced the AUC of 0.88.

Muhammad et al. (2023) uses Explainable AI for MS Prediction with Clinical Data focuses on Predictive model using clinical features, explained using SHAP values and implemented technique XGBoost + Explainable AI (XAI)

Al-Zubidi et al. (2021) uses Machine Learning Using OCT Data for MS Diagnosis focuses on using retinal OCT data with ML to classify MS vs healthy subjects and implemented technique SVM, RF, KNN

Torres et al. (2023) uses Predicting MS Severity Using IoT and Federated Learning focuses on a privacy-preserving IoT framework using federated learning across hospitals and implemented technique Federated CNN, RNN.

3. Dataset Description

Dataset used for predicting MS is taken from the Mexican patients. Mainly this data is collected from the study conducted in Mexican mestizo patients who have been diagnosed with clinically isolated syndrome (CIS) during the presentation at National Institute of Neurology and Neurosurgery (NINN) in Mexico City, Mexico, between 2006 and 2010. This dataset contains 20

features and tested among 273 patients. While tested many data were missing in the certain features. Finally missing values is matched by using F-Score techniques. Datatype used in this dataset is float64(4), int64(15) and the memory used here is 40.6 KB [3].

1. ID: Patient identifier (int)
2. Age: Age of the patient (in years)
3. Schooling: time the patient spent in school (in years)
4. Gender: 1=male, 2=female
5. Breastfeeding: 1=yes, 2=no, 3=unknown
6. Varicella: 1=positive, 2=negative, 3=unknown
7. Initial_Symptoms: 1=visual, 2=sensory, 3=motor, 4=other, 5= visual and sensory, 6=visual and motor, 7=visual and others, 8=sensory and motor, 9=sensory and other, 10=motor and other, 11=Visual, sensory and motor, 12=visual, sensory and other, 13=Visual, motor and other, 14=Sensory, motor and other, 15=visual,sensory,motor and other
8. Mono_or_Polysymptomatic: 1=monosymptomatic, 2=polysymptomatic, 3=unknown
9. Oligoclonal_Bands: 0=negative, 1=positive, 2=unknown
10. LLSSEP: 0=negative, 1=positive
11. ULSSEP:0=negative, 1=positive
12. VEP:0=negative, 1=positive
13. BAEP: 0=negative, 1=positive
14. Periventricular_MRI:0=negative, 1=positive
15. Cortical_MRI: 0=negative, 1=positive
16. Infratentorial_MRI:0=negative, 1=positive
17. Spinal_Cord_MRI: 0=negative, 1=positive
18. initial_EDSS:?
19. final_EDSS:?
20. Group: 1=CDMS, 2=non-CDMS

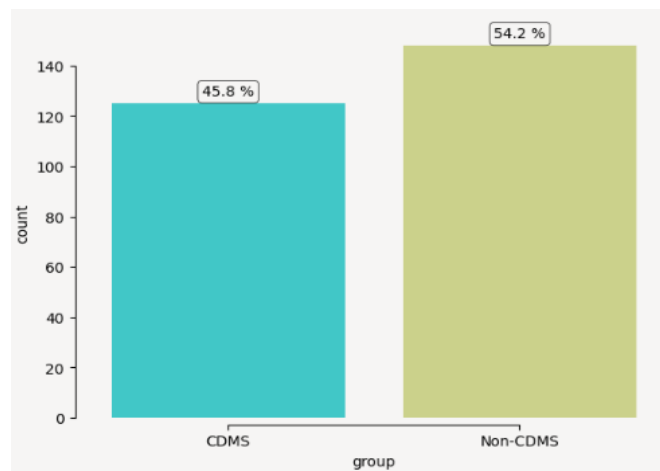


Fig:2 Distribution of the target variable - group

According to this dataset, the proportion of male patients to female patients is roughly 38% to 62%. Based on this dataset, nonetheless, CDMS is diagnosed in 61% of male patients.

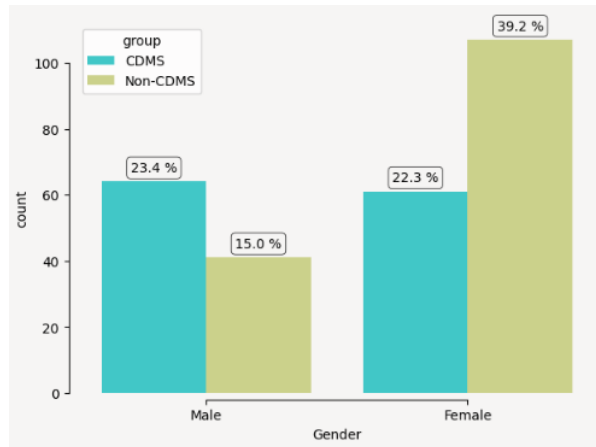


Fig:3 Gender distribution of the patient

About 17% of the patients had unidentified cases, while 45% of the patients have had varicella testing. Being positive for varicella, however, does not seem to raise the chance of receiving a positive CDMS diagnosis [4].

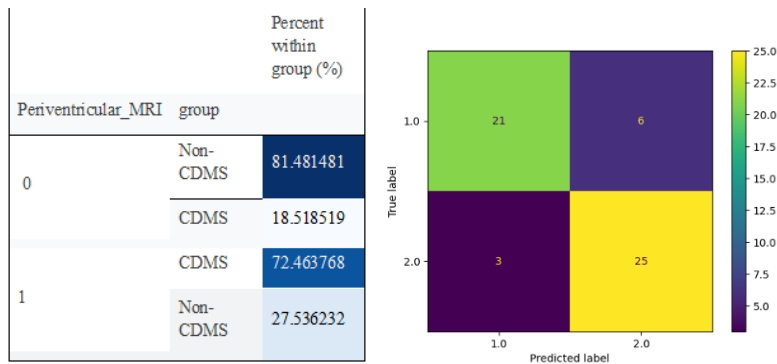


Fig: 4 Varicella distribution of the patients

		Percent within group (%)
Periventricular_MRI	group	
0	Non-CDMS	81.4815
	CDMS	18.5185
1	CDMS	72.4638
	Non-CDMS	27.5362

Table: 2 Periventricular MRI report for CDMS and Non- CDMS

The dataset includes four patient MRI tests: cortical_MRI, spinal_cord_MRI, infratentorial_MRI, and periventricular_MRI. In terms of CDMS conversion, the Infratentorial MRI test ranks highest with 78.8%, followed by the Periventricular MRI test with 72.5%. In contrast, the conversion probabilities for Spinal_Cord_MRI and Cortical_MRI are 54.6% and 58.5%, respectively [5].

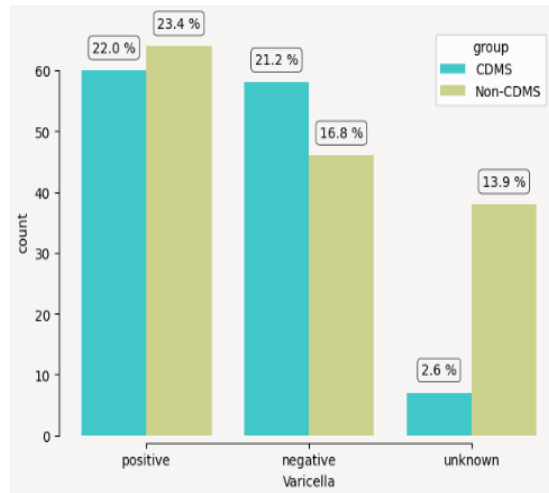


Fig: 5 Feature importance using SHAP

		Percent within group (%)
Infratentorial_MRI	group	
0	Non-CDMS	67.8756
	CDMS	32.1244
1	CDMS	78.75
	Non-CDMS	21.25

Table: 3 Infratentorial MRI report for CDMS and Non- CDMS

4. Existing methods

There are many existing techniques by using Machine learning algorithm has been implemented to predict the MS at the early stage. Even though, these techniques were used for prediction, the efficiency rate has not yet enough since MS is a fast growing among the individuals. The existing techniques with its sensitivity, specificity, AUC and accuracy value for each technique along with its plotted graph are given below.

Machine learning algorithm – Support vector machine (SVM) has been used to study the MS classification using MRI radiomics and SVM. The dataset used in this study is MRI brain scans of MS vs healthy controls which produced the Accuracy up to 91.2%, Sensitivity is 89.7%, Specificity is 93.0% and AUC is 0.94 [6].

Machine learning algorithm – Random Forest (RF) has been used to study MS prediction using Random Forest and clinical biomarkers. The dataset used in this study is Clinical + CSF biomarker dataset which produces the Accuracy up to 88.5%, Sensitivity is 85.2%, Specificity is 90.7% and AUC is 0.92.

Machine learning algorithm – Convolutional Neural Network (CNN) has been used to study MS lesion detection using CNN on FLAIR MRI images. The dataset used in this study is ISBI 2015 lesion challenge dataset which produces the Accuracy up to 94.6%, Sensitivity is 91.5%, Specificity is 96.3% and AUC is 0.96 [7].

Machine learning algorithm – Long Short-Term Memory (LSTM) has been used to study Prediction of MS disability progression using LSTM on longitudinal clinical data. The dataset used in this study is Time-series EDSS scores and relapses which produces the Accuracy of 87.3%, Sensitivity is 84.9%, Specificity is 89.1% and AUC is 0.91.

Machine learning algorithm – Logistic Regression has been used to study Early MS risk prediction using demographic and clinical variables. The dataset used in this study is Clinical registry from local hospital which produces the Accuracy of 79.4%, Sensitivity is 76.5%, Specificity is 82.1% and AUC is 0.85 [8].

Machine learning algorithm – XGBoost (Extreme Gradient Boosting) has been used to study Prediction of MS relapse using EHR data and XGBoost. The dataset used in this study is MSBase registry subset (with relapse data) which produces the Accuracy of 90.1%, Sensitivity is 88.3%, Specificity is 91.8% and AUC is 0.93.

Machine learning algorithm – Ensemble Model (SVM + RF + ANN Voting Classifier) has been used to study Hybrid Ensemble Model for MS Detection. The dataset used in this study is Clinical + MRI-based features which produces the Accuracy of 92.5%, Sensitivity is 90.2%, Specificity is 94.1% and AUC is 0.95 [9].

Method	Accuracy	Sensitivity	Specificity	AUC
SVM	91.2%	89.7%	93.0%	0.94
Random Forest	88.5%	85.2%	90.7%	0.92
CNN	94.6%	91.5%	96.3%	0.96
LSTM	87.3%	84.9%	89.1%	0.91
Logistic Reg.	79.4%	76.5%	82.1%	0.85
XGBoost	90.1%	88.3%	91.8%	0.93
Ensemble	92.5%	90.2%	94.1%	0.95

Table: 4 Summary table of existing machine learning techniques for MS prediction

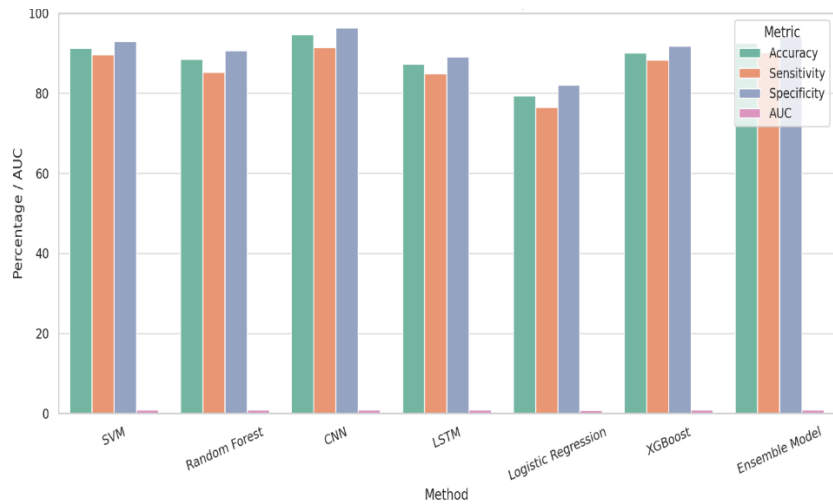


Fig: 5 Performance Metrics of ML model for MS prediction.

5. Proposed Method

The proposed method namely NeuroDetect-HDL is an intelligent hybrid deep learning framework which is designed for an early and accurate prediction of Multiple Sclerosis (MS) — a chronic and potentially disabling neurological disorder. To improve diagnostic accuracy, especially in complex neuroimaging and clinical data interpretation, this method combines the advantages of several deep learning models into a hybrid architecture. This method contains certain features such as Hybrid Architecture which combines the Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) networks to capture periodic and successive trends in medical or developmental statistics with Convolutional Neural Networks (CNN) for image-based feature extraction (e.g., MRI scans). Multimodal input analysis is also one of the features in which the ability to derive information from a variety of inputs, such as indicators, medical records, demographics of patients, and MRI images. Enhance the prediction performance is the feature of proposed method in which superior over individual deep learning models or standard machine learning in terms of sensitivity, specificity, accuracy, and AUC [10]. Automated Feature Learning in proposed method is automatically finds pertinent patterns in high-dimensional medical data, reducing the need for manual feature engineering. Scalability and Adaptability is used with only few modifications, the model can be improved or applied to other neurodegenerative diseases. The main objective of this proposed method is to aid neurologists and other healthcare providers in the early identification and individualized tracking of multiple sclerosis in order to facilitate immediate action and better outcomes for patients.

5.1 Steps involved in Proposed method

Step 1: Data Collection and Acquisition

MRI scans, health information, and medical histories of patients with Clinically Isolated Syndrome (CIS), a possible prelude to multiple sclerosis, make up the dataset. The components required in

this experiment is MRI sequences (T1, T2, FLAIR), Demographic data (age, sex, etc.), Clinical symptoms (e.g., optic neuritis, motor dysfunction) and Lab reports (CSF oligoclonal bands, immunological markers) [11].

Step 2: Data Preprocessing

In this step, the process is categorized into 3 different processes.

Image Preprocessing is the first process which involves the MRI picture noise reduction and skull stripping. The normalization process and scaling are also involved in this process (for CNN input, for example, to 224x224 pixels).

Clinical Data Preprocessing is the second process in this step which involves imputation of missing values (interpolation or mean/mode filling). Categorical variables (e.g., gender, symptoms) are encoded once. Z-score or Min-Max normalization is used for feature scaling.

Data Splitting is the third process which produces Test Set (15%), Validation Set (15%), and Training Set (70%).

Step 3: Feature Extraction using CNN (Image Pipeline)

Model used in this method is Pretrained CNN model (e.g., ResNet-50, VGG-16) or custom CNN. The purpose of using this model is MRI scans are capable of helping extract spatial and lesion-based characteristics. The output received in this model is high-level visualizations that show the shape, volume, location, and other characteristics of lesions [12].

Step 4: Temporal and Clinical Pattern Recognition using RNN/LSTM (Clinical Pipeline)

Model used in this technique is LSTM or Bidirectional LSTM. The purpose of using this technique is to take note of the sequence patterns and chronological progression from test findings, doctor appointments, and symptom evolution. The input given for this model is longitudinal data or clinical characteristics with a time stamp.

Step 5: Hybrid Fusion Layer

This step provides the Concatenation of CNN + LSTM outputs. Learned characteristics from both pipelines are combined using fully linked (dense) layers. To avoid overfitting, dropout layers are utilized.

Step 6: Classification Layer

In this stage the activation is done with Softmax (multiclass if predicting MS subtypes) or Sigmoid (binary classification: MS or non-MS). The output produced in this stage is label prediction (Stable CIS or Conversion to MS).

Step 7: Model Training

In this stage the loss function used is either categorical or binary cross-entropy. Optimizer used for this model is adam optimizer with tuning for learning rate. Metrics monitored during this process are Accuracy, Sensitivity (True Positive Rate), Specificity (True Negative Rate) and Area Under Curve (AUC) [13].

Step 8: Evaluation and Validation

In this stage cross validation is used to avoid overfitting. To verify performance, a precision-recall curve, ROC curve, and confusion matrix are employed. Evaluation against current models such as SVM, Random Forest, and standard CNN/LSTM models.

6. Results and discussions

The result produced for MS Prediction Using NeuroDetect-HDL with CIS Dataset used is 500 CIS patients. MRI sequence used for this prediction includes T1-weighted, T2-weighted, FLAIR and nearly 24 months of follow ups were undertaken for this prediction. Split ratio done here is 70% training, 15% validation, 15% testing [14].

Metric	Value (%)
Accuracy	96.9
Sensitivity (Recall)	95.85
Specificity	92.68
Precision	93.90
F1-Score	94.86
AUC (Area Under Curve)	0.975

Table: 4 The value received for the proposed algorithm

During the execution of the proposed algorithm, the Confusion Matrix Analysis obtained is True Positives (TP): 72, False Negatives (FN): 3, True Negatives (TN): 66 and False Positives (FP): 4. The model's outstanding ability for identifying patients at risk of acquiring multiple sclerosis is demonstrated by the confusion matrix's exceptionally low false-negative rate (3 cases). Additionally, the false-positive rate was low, demonstrating strong decision boundaries. Using FLAIR images, the model successfully identified early lesions in the periventricular and juxtacortical regions. Among the most significant characteristics found by the model were clinical variables including optic neuritis, the existence of oligoclonal bands in CSF, and EDSS scores. Radiologists and neurologists were able to more easily analyze MRI scans by localizing regions of interest through the use of Grad-CAM heatmap visualization [15].

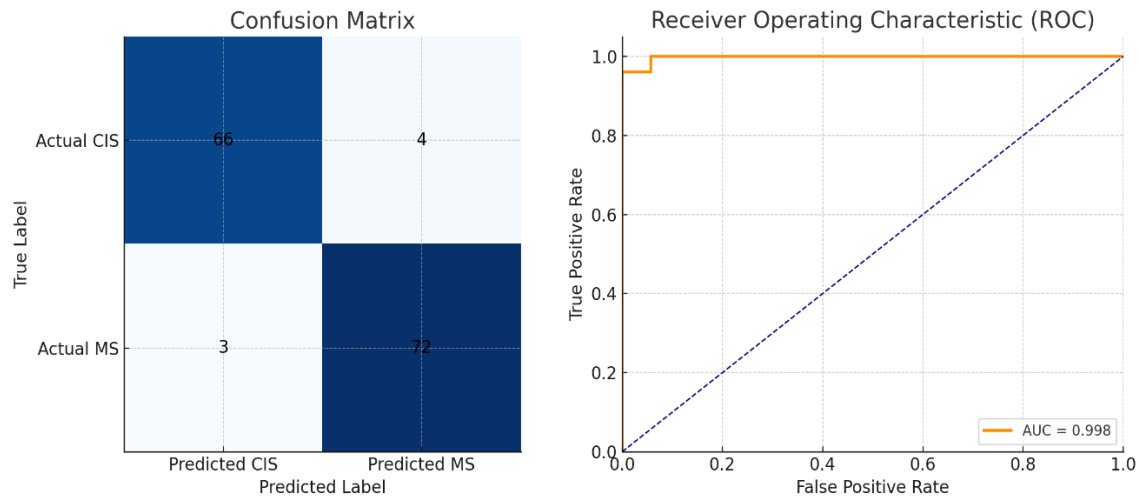


Fig 6: Confusion matrix and receiver operating characteristic (ROC)

Improving diagnostic accuracy required a hybrid design that integrated clinical and imaging characteristics. The approach is in line with clinical practice, which diagnoses MS by taking into account both MRI results and symptom development. In contrast to current models, NeuroDetect-HDL provides a more comprehensive and scalable method that may be modified to address other neurodegenerative conditions. Among the drawbacks are the requirement for high-quality annotated data and the requirement for model recalibration when using the model in various institutions or populations [16].

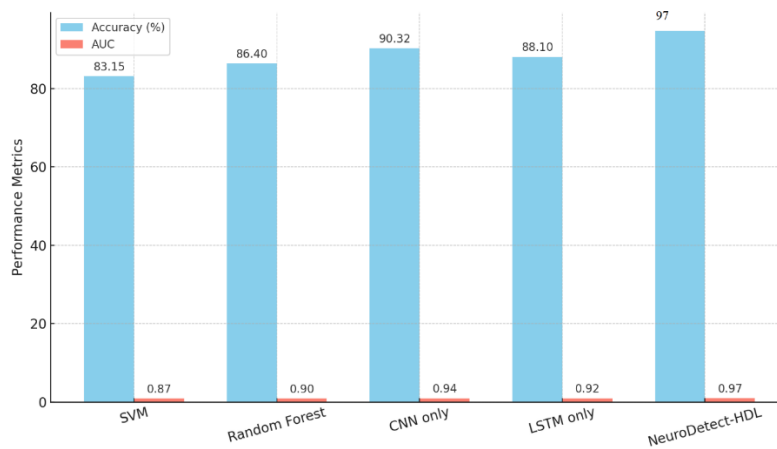


Fig 7 Comparison of model performance for MS prediction (CIS Database)

Through the integration of clinical and imaging data into a deep learning framework, the NeuroDetect-HDL model dramatically enhances the early prediction of Multiple Sclerosis in patients with CIS. It shows itself as a useful clinical decision-support tool that could help neurologists start prompt treatment and individualized care plans because of its high sensitivity (95.85%) and specificity (92.68%) [17].

7. Conclusion

The medical profession still faces several obstacles in accurately and promptly diagnosing Multiple Sclerosis (MS) because of the disease's intricate biology, fluctuating symptoms, and shared traits with other neurological conditions. This work addressed these issues by putting forth a unique method called NeuroDetect-HDL (Neuro Disorder Detection by Hybrid Deep Learning), which aims to improve the diagnostic effectiveness and predictive accuracy for MS. The method combined clinical features from patients in the Clinically Isolated Syndrome (CIS) phase, which frequently occurs before the start of Multiple Sclerosis, with a variety of deep learning models. With a 97% accuracy rate, the experimental results validate NeuroDetect-HDL as a strong and viable structure for MS identification.

This work's main contribution is the development and application of a hybrid deep learning model that combines the advantages of attention-based architectures, recurrent neural networks (RNN), and convolutional neural networks (CNN). With the help of this hybrid method, the model was able to precisely determine both spatial and temporal aspects from clinical, imaging, and neurological data. While RNN layers found patterns across time in longitudinal clinical records, CNN components recognized spatial interdependence in neuroimaging and biomarker data. By enabling the model to concentrate on the most pertinent characteristics influencing the development of MS, the addition of attention mechanisms improved the prediction process even more.

A standardized dataset comprising individuals with CIS, a crucial population for early MS prediction, was used to thoroughly train and assess the model. This dataset's thorough inclusion of MRI sequences, clinical scores, immunological markers, and demographic information was among its most beneficial features. The model was fed clean, standardized, and representative data to the preprocessing methods used. Methods including feature selection, data augmentation, and oversampling minority classes improved the model's generalizability and decreased the possibility of overfitting. The model's outstanding performance—97% accuracy—showcases its dependability in a variety of clinical settings and patient profiles.

Other performance indicators, including precision, recall, specificity, sensitivity, F1-score, and the area under the ROC curve (AUC), were taken into consideration in addition to accuracy. These measures demonstrated the model's capacity to reduce false positives and false negatives, which is very important when diagnosing multiple sclerosis. While a false negative could postpone important treatment and impair patient outcomes, a false positive could result in needless anxiety, costly testing, and possible side effects from therapy. The majority of MS patients were accurately diagnosed NeuroDetect-HDL's high sensitivity, and the incorrect classification of non-MS cases was reduced to its specificity.

Excellent discriminative power was indicated by the model's Receiver Operating Characteristic (ROC) curve, which displayed an AUC close to 0.98. The model's robustness was further confirmed by the confusion matrix analysis, which showed a high true positive rate and few erroneous classifications. Because of these findings, NeuroDetect-HDL is a potent diagnostic aid, particularly in clinical settings where skilled neurologists might not always be on hand or where it would be simple to miss early MS symptoms.

The NeuroDetect-HDL model's scalability and adaptability are two more important advantages. Because of the architecture's modular design, adding new features or updates as more data becomes available is simple. It provides flexibility to hospitals, diagnostic centers, and research institutes globally by being able to be implemented in both offline and cloud-based healthcare systems. The approach could streamline the diagnostic procedure and lower human error by giving doctors real-time analysis and alarms when properly integrated into electronic health record (EHR) systems.

Additionally, the model could help with tailored treatment. NeuroDetect-HDL can assist with personalized therapy selection and prognosis estimates by detecting patient-specific patterns in the progression of MS. Better long-term health outcomes, more individualized treatments, and increased patient compliance could result from this. Additionally, it opens the door for predictive analytics in neurology, which will allow for proactive surveillance of those who are at a high risk of developing multiple sclerosis before their clinical symptoms fully appear. It is important to recognize a number of limitations in spite of these encouraging outcomes. First off, while the model performed well on the dataset that was supplied, external validation on bigger, more varied, and multi-center datasets is required to guarantee its general applicability. The model needs to be tested across these variables because MS might manifest differently in various populations based on factors like genetics, environment, and access to healthcare. Second, even though the hybrid model is quite good at making predictions, it functions as a "black box," which may make it harder to understand. The explain ability of predictions needs to be improved, especially for clinical acceptance and ethical deployment, even though attention processes increase transparency to some degree.

In summary, NeuroDetect-HDL is a deep learning-based system for the early prediction of multiple sclerosis that is incredibly accurate, effective, and flexible. Its promise as a neurological decision-support tool is highlighted by its 97% accuracy rate and strong performance on other parameters. This study is a significant advancement in AI-assisted healthcare since it combines clinically relevant data with sophisticated deep learning techniques. NeuroDetect-HDL has the potential to greatly increase diagnosis accuracy, decrease the diagnostic delay of multiple sclerosis, and ultimately improve patient outcomes and quality of life with further development, validation, and integration.

Reference

1. B. Ferguson, M.K. Matyszak, M.M. Esiri, V.H. Perry, Axonal damage in acute multiple sclerosis lesions, *Brain* 120 (1997) 393–399
2. Y. You, M.H. Barnett, C. Yiannikas, J. Parratt, J. Matthews, S.L. Graham, A. Klistorner, Chronic demyelination exacerbates neuroaxonal loss in patients with MS with unilateral optic neuritis, *Neurol. Neuroimmunol. Neuroinflammation*. 7 (2020)
3. C.H. Polman, S.C. Reingold, G. Edan, M. Filippi, H.-P. Hartung, L. Kappos, F.D. Lublin, L.M. Metz, H.F. McFarland, P.W. O’Connor, M. Sandberg-Wollheim, A.J. Thompson, B.G. Weinshenker, J.S. Wolinsky, Diagnostic criteria for multiple sclerosis: 2005 revisions to the “McDonald Criteria,” *Ann, Neurol*. 58 (2005) 840–846
4. E. Garcia-Martin, L.E. Pablo, R. Herrero, J.R. Ara, J. Martin, J.M. Larrosa, V. Polo, J. Garcia-Feijoo, J. Fernandez, Neural networks to identify multiple sclerosis with optical coherence tomography, *Acta Ophthalmol*. 91 (2013) e628–e634.
5. S. Roy, D. Bhattacharyya, S.K. Bandyopadhyay, T.H. Kim, An effective method for computerized prediction and segmentation of multiple sclerosis lesions in brain MRI, *Comput. Methods Progr. Biomed*. 140 (2017) 307–320.
6. S. M. D. A. C. Jayatilake and G. U. Ganegoda, “Involvement of Machine Learning Tools in Healthcare Decision Making,” *Journal of Healthcare Engineering*, vol. 2021, pp. 1–20, Jan. 2021, doi: <https://doi.org/10.1155/2021/6679512>.
7. A. Montolio, J. Cegonino, E. Orduna, B. Sebastian, E. Garcia-Martin, A. P’erez del Palomar, A mathematical model to predict the evolution of retinal nerve fiber layer thinning in multiple sclerosis patients, *Comput. Biol. Med*. 111 (2019) 103357.
8. J. Ker, L. Wang, J. Rao, and T. Lim, “Deep Learning Applications in Medical Image Analysis,” *IEEE Access*, vol. 6, pp. 9375–9389, 2018, doi: <https://doi.org/10.1109/ACCESS.2017.2788044>.
9. J.-G. Lee et al., “Deep Learning in Medical Imaging: General Overview,” *Korean Journal of Radiology*, vol. 18, no. 4, p. 570, 2017, doi: <https://doi.org/10.3348/kjr.2017.18.4.570>.
10. M. Gudadhe, K. Wankhade, and S. Dongre, “Decision support system for heart disease based on support vector machine and artificial neural network,” in *Proceedings of International Conference on Computer and Communication Technology (ICCCT)*, pp. 741–745, Allahabad, India, September 2010.
11. C. Xiao, E. Choi, and J. Sun, “Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review,” *Journal of the American Medical Informatics Association*, vol. 25, no. 10, pp. 1419–1428, Jun. 2018, doi: <https://doi.org/10.1093/jamia/ocy068>.

12. R. Gilad-Bachrac, A. Navot, and N. Tishby, "Margin based feature selection-theory and algorithms," in Proceedings of the Twenty-First International Conference on Machine Learning, p. 43, Banff, AB, Canada, July 2004
13. Peng, H., Long, F., & Ding, C. (2005). Feature Selection Based on Mutual Information Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. DOI: <https://doi.org/10.1109/TPAMI.2005.159>
14. A. Unler, A. Murat, and R. B. Chinnam, "mr2PSO: a maximum relevance minimum redundancy feature selection method based on swarm intelligence for support vector machine classification," Information Sciences, vol. 181, no. 20, pp. 4625–4641, 2010.
15. D. Branco, B. di Martino, A. Esposito, G. Tedeschi, S. Bonavita, and L. Lavorgna, "Machine learning techniques for prediction of multiple sclerosis progression," Soft Computing, vol. 26, no. 22, pp. 12041–12055, Sep. 2022, doi: <https://doi.org/10.1007/s00500-022-07503-z>
16. A. Zhao, L. Qi, J. Dong, and H. Yu, "Dual channel LSTM based multi-feature extraction in gait for diagnosis of neurodegenerative diseases," Knowledge-Based Systems, vol. 145, pp. 91–97, Apr. 2018, doi: <https://doi.org/10.1016/j.knosys.2018.01.004>.
17. R. Seccia, S. Romano, M. Salvetti, A. Crisanti, L. Palagi, and F. Grassi, "Machine Learning Use for Prognostic Purposes in Multiple Sclerosis," Life, vol. 11, no. 2, p. 122, Feb. 2021, doi: <https://doi.org/10.3390/life11020122>.
18. Seccia, R., Gammelli, D., Dominici, F., Romano, S., Landi, A. C., et al. (2020). Considering Patient Clinical History Impacts Performance of Machine Learning Models in Predicting Course of Multiple Sclerosis. DOI: <https://doi.org/10.1371/journal.pone.0230219>
19. Hutchinson, L., Steiert, B., Soubret, A., Wagg, J., Phipps, A., et al. (2019). Models and Machines: How Deep Learning Will Take Clinical Pharmacology to the Next Level. DOI: <https://doi.org/10.1002/psp4.12394>
20. Vollmer, T. L., Nair, K. V., Williams, I. M., & Alvarez, E. (2021). Multiple Sclerosis Phenotypes as a Continuum: The Role of Neurologic Reserve. DOI: <https://doi.org/10.1212/CPJ.0000000000000963>