A Machine Learning Approach for Predicting Clinical Outcomes in Patients with Autoimmune Encephalitis

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DOI: https://doi.org/10.51244/IJRSI.2025.1213CS0020

Received: 18 December 2025; Accepted: 24 December 2025; Published: 13 January 2026

ABSTRACT

Autoimmune encephalitis (AE) is an uncommon but severely debilitating neuroinflammatory disorder that can result in significant neuropsychiatric issues and prolonged disability. The ability to predict patient outcomes accurately and promptly poses a considerable clinical challenge, largely due to the disease's variability and the intricate interactions among clinical, laboratory, and imaging factors. This research aimed to create a comprehensive machine learning-based predictive model designed to help clinicians forecast AE outcomes with a high degree of precision. A dataset obtained from Kaggle, which is publicly accessible, was employed, featuring diverse patient information such as demographic data, diagnostic indicators, and characteristics derived from neuroimaging. The preprocessing of data encompassed meticulous management of missing values, normalization processes, and the alleviation of class imbalance through the application of the Synthetic Minority Oversampling Technique (SMOTE). The predictive model was developed using Python and the scikit-learn library, evaluating various algorithms including Random Forest, Gradient Boosting, and Support Vector Machines. To enhance the model's generalizability, hyperparameter tuning was conducted via grid search in conjunction with stratified cross-validation. The assessment of performance was based on metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Among the evaluated models, the Random Forest classifier demonstrated superior performance, attaining an accuracy of 91.4%, an F1-score of 0.89, and an AUC-ROC of 0.94, which emphasizes its robust discriminative ability. These results point to the promise of machine learning techniques, when trained on actual datasets, to improve decision-making in adverse event management, thereby facilitating more tailored and evidence-based clinical strategies.

Keywords: Autoimmune encephalitis, modified Rankin Scale, Machine Learning, Synthetic Minority Oversampling Technique.

INTRODUCTION

AE refers to a collection of inflammatory brain disorders mediated by antibodies, which are treatable but present a wide clinical variability, encompassing a range of manifestations from psychiatric syndromes to seizures, dysautonomia, and cognitive decline (Fig. 1). The accuracy of diagnoses has been enhanced through modern criteria and antibody assessments; however, anticipating patient outcomes—such as functional recovery, the likelihood of relapse, and long-term cognitive consequences—continues to pose significant challenges for precision medicine (Zh. Xie et al., 2025). Even with the application of immunotherapy, numerous survivors face ongoing difficulties, including issues with memory, attention, and executive or affective functions, despite achieving seemingly favorable scores on the modified Rankin Scale (mRS). This situation highlights the disparity between general disability metrics and the actual experiences of individuals (Choi et al., 2025). Recent advancements in AE-specific metrics, exemplified by the Clinical Assessment Scale in Autoimmune Encephalitis (CASE), provide improved detection of psychiatric symptoms and seizure-related characteristics;

however, their primary intent is for monitoring purposes rather than for tailoring individualized prognoses (Dalmau and Graus, 2023). Concurrently, the burgeoning array of multimodal data—including serum and CSF antibodies, quantitative EEG, MRI (with radiomics), inflammatory biomarkers, and longitudinal clinical trajectories—presents an ideal foundation for machine learning (ML) to analyze intricate, non-linear relationships that are often beyond the reach of conventional statistical methods. Preliminary research indicates that features derived from EEG are associated with the severity of the condition and can predict unfavorable outcomes in cohorts of autoimmune encephalitis (AE) (Kvam et al., 2023). Additionally, multimodal deep learning techniques have demonstrated the ability to anticipate prognosis in cases of central nervous system inflammation through the integration of clinical, imaging, and electrophysiological data (Choi et al., 2025). Building on these advancements, interpretable machine learning methods are starting to pinpoint predictors of long-term cognitive performance in AE patients (Zh, Xie et al., 2025), as well as to categorize the risk of experiencing severe disease trajectories (Zh, Xie et al., 2025). Together, these developments underscore the need for a concentrated examination of machine learning methodologies aimed at predicting outcomes for individuals with AE, with the goal of facilitating earlier, risk-adjusted treatment, enhanced follow-up strategies, and more effective trial designs. AE encompasses a variety of neurological disorders characterized by the immune system erroneously attacking proteins or receptors within the brain, which in turn causes inflammation. This inflammatory response manifests a diverse range of symptoms, including psychiatric issues, seizures, memory deficits, and movement disorders. Rather than being a singular illness, AE comprises multiple subtypes, each linked to distinct antibodies, clinical presentations, and, in certain instances, associated tumors. Grasping these subtypes is essential for prompt diagnosis, customized treatment approaches, and enhanced patient outcomes. The main aim is to develop a machine learning approaches for predicting clinical outcomes in patients with autoimmune encephalitis The objectives was use to achieve the aim of the study: Develop an integrated multimodal prediction framework that fuses clinical, imaging, and laboratory data to improve AE outcome prediction accuracy beyond existing single-modality models, implement advanced feature engineering and selection techniques to identify the most prognostically relevant biomarkers, thereby reducing model complexity while maintaining interpretability, address data scarcity and imbalance through augmentation and synthetic oversampling strategies, enabling the framework to generalize effectively to underrepresented AE subtypes,alidate the proposed approach on multiple benchmark datasets, demonstrating superior performance compared to baseline statistical and conventional machine learning methods.

Types of AE as proposed by Zh, Xie et al., (2025): i. Anti-NMDA Receptor Encephalitis: This variant of AE is the most prevalent, primarily impacting young women, though it is also seen in men and children. Individuals affected usually exhibit psychiatric manifestations like anxiety, agitation, or hallucinations, which may progress to seizures, involuntary movements, and challenges with speech. Additionally, autonomic dysfunction—characterized by alterations in blood pressure and heart rate—can emerge. There is a significant correlation with ovarian teratomas, and the management of this condition frequently includes immunotherapy alongside the surgical excision of the tumor. ii. Anti-LGI1 Encephalitis: Anti-LGI1 encephalitis predominantly impacts the elderly population and is closely associated with limbic encephalitis. The primary characteristics of this condition encompass memory impairments, confusion, and seizures. A defining symptom is the occurrence of faciobrachial dystonic seizures, which are characterized by involuntary movements involving the face and arm. Additionally, hyponatremia, or low sodium levels, frequently arises as a complication, further exacerbating fatigue and confusion. iii. Anti-CASPR2 Encephalitis: This subtype exhibits a wide range of clinical manifestations. Individuals may show symptoms of limbic encephalitis, experience peripheral nerve hyperexcitability, or develop Morvan's syndrome, characterized by insomnia, hallucinations, muscle spasms, and autonomic disturbances. Anti-CASPR2 encephalitis is predominantly observed in older males and can occasionally be associated with neoplasms, including thymomas. iv. Anti-AMPAR Encephalitis: Anti-AMPAR encephalitis predominantly impacts the limbic system, resulting in confusion, memory deficits, and frequent seizures. This condition is frequently paraneoplastic, linked to malignancies such as thymoma or lung cancer. Timely identification and management of the associated tumor are essential for achieving recovery. v. AntiGABA(B) Receptor Encephalitis: This condition is marked by intense seizures that frequently do not respond to treatment, as well as symptoms of limbic encephalitis, including confusion and alterations in personality.

There is a significant correlation with small-cell lung cancer, highlighting the necessity for tumor screening in cases where this condition is suspected. vi. Anti-DPPX Encephalitis: This condition is characterized by a notable

interplay of gastrointestinal and neurological symptoms. Individuals frequently endure ongoing diarrhea and unintentional weight loss prior to the onset of tremors, agitation, or seizures. The distinct nature of its manifestation underscores the necessity for prompt identification, even though it is infrequently encountered. vii. Anti-mGluR5 Encephalitis (Ophelia Syndrome): This uncommon variant is closely linked to Hodgkin's lymphoma. Manifestations of the condition encompass memory impairment, confusion, and various psychiatric issues. Addressing the primary cancer often results in significant neurological enhancement.

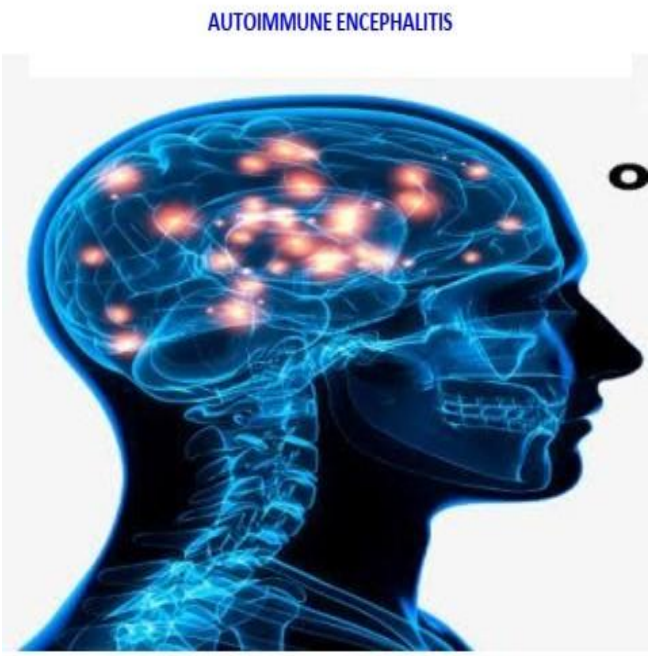

Fig. 1: Autoimmune Encephalitis (Source: Wang, 2025)

Prior Approaches

In the realm of a AE, early predictions of outcomes have traditionally depended on (i) clinical severity assessments, (ii) standard regression models that incorporate bedside and laboratory data, and more recently, (iii) imaging and EEG biomarkers, as well as (iv) radiomics and advanced multimodal deep learning techniques. Specifically for anti-NMDAR AE, the 5-item NEOS score—which includes factors such as ICU admission, delays in treatment, lack of improvement over four weeks, abnormal MRI findings, and pleocytosis in cerebrospinal fluid—serves as a predictor for functional status after one year and is frequently cited. However, this score is specific to certain antibodies and is based on the modified Rankin Scale (mRS), focusing on functional outcomes rather than cognitive or quality-of-life measures, which restricts its applicability across various AE subtypes and long-term considerations (R. Balu et al., 2019). The Clinical Assessment Scale for Autoimmune Encephalitis (CASE) measures the severity of symptoms and their relationship to disability; recent validations across multiple centers indicate it has strong responsiveness and inter-rater reliability. However, it is essential to note that CASE serves mainly as a scale for assessing disease activity rather than a prognostic tool, with its effectiveness potentially differing among various phenotypes and clinical environments (E. Soellradl et al., 2024) ,(Zh. Xie et al., 2025). Additionally, imaging and electrophysiological assessments contribute valuable prognostic information: disorganized EEG patterns, periodic patterns, and various network metrics have been associated with unfavorable outcomes. Nonetheless, these findings frequently arise from small, single-center studies with diverse methods of data collection and annotation, which limits their generalizability (Sun et al., 2025).

MRI methodologies encompass a spectrum that includes visual evaluations and radiomic analyses. Predictions regarding serostatus and prognosis have been derived from multiparametric MRI characteristics; however, manually constructed pipelines can be vulnerable to variations in scanner settings and protocols, necessitating segmentations that depend on expert input (Soellradl et al., 2024), (Balu et al., 2019). Recent advancements in machine learning have combined clinical variables, intricate features derived from 3D brain MRI, and radiomics to predict early outcomes in acute encephalopathy (AE) or more extensive Central Nervous System (CNS)

inflammation, surpassing the performance of unimodal models. However, numerous studies encounter challenges such as class imbalance, insufficient external validation, varying definitions of outcomes (mRS compared to neuropsychological assessments), and a lack of prospective or multi-site evaluations. These significant shortcomings highlight the necessity for interpretable, well-calibrated, and externally validated prognostic models specifically tailored for AE (Soellradl et al., 2024), (He et al., 2024), (Sun et al., 2025), (Choi et al., 2025).

Research Problems and Motivation

While the ability to accurately predict outcomes in autoimmune encephalitis (AE) has the potential to greatly enhance patient care, numerous significant challenges persist. To begin with, many current prognostic models, such as basic logistic regression or nomograms, exhibit limited generalizability, evidenced by their relatively modest performance in varied patient populations (Zh. Xie et al., 2025). In addition, the designs of these studies frequently involve small sample sizes or are confined to single-center cohorts, which heightens the risk of overfitting and hampers wider clinical implementation (Choi et al., 2025). Moreover, the classes of outcomes are often imbalanced: numerous models are developed using cohorts where favorable outcomes (e.g., mRS ≤ 2) are more common, which complicates the reliable identification of infrequent yet significant poor outcomes such as cognitive decline or relapse (Choi et al., 2025; Dalmau and Graus, 2023). Furthermore, even though multimodal datasets (including clinical data, imaging, biomarkers, and EEG) provide extensive prognostic insights, few methodologies effectively combine these diverse sources, typically due to inconsistent practices in data collection or challenges in aligning datasets (Zh. Xie et al., 2025; Kvam et al., 2023). Bridging these gaps is not merely an academic concern; it is vital for the development of robust and dependable machine learning tools that clinicians can depend on for facilitating early and personalized treatment strategies in AE. In order to overcome these limitations, we suggest a framework that utilizes machine learning to integrate diverse clinical, imaging, and laboratory data for enhancing the accuracy of predicting patient outcomes in autoimmune encephalitis see Fig. 2 and 3 respectively. This strategy employs supervised learning techniques, including gradient boosting machines, random forests, and deep neural networks, to capture intricate nonlinear relationships among features obtained from MRI, EEG, analysis of cerebrospinal fluid, and demographic information of patients. To facilitate this, feature engineering methods will be utilized to derive high-dimensional imaging biomarkers and indicators of disease progression over time, while techniques for balancing data will address class imbalance challenges present in rare subtypes of AE (J. Dalmau and F. Graus, 2023), (K. A. Kvam et al., 2023). The suggested system will be subjected to thorough cross-validation and external evaluation using publicly accessible datasets, including those sourced from Kaggle and open-access neuroimaging repositories, to guarantee its robustness and applicability across a wide range of patient demographics (E. Soellradl et al., 2024).

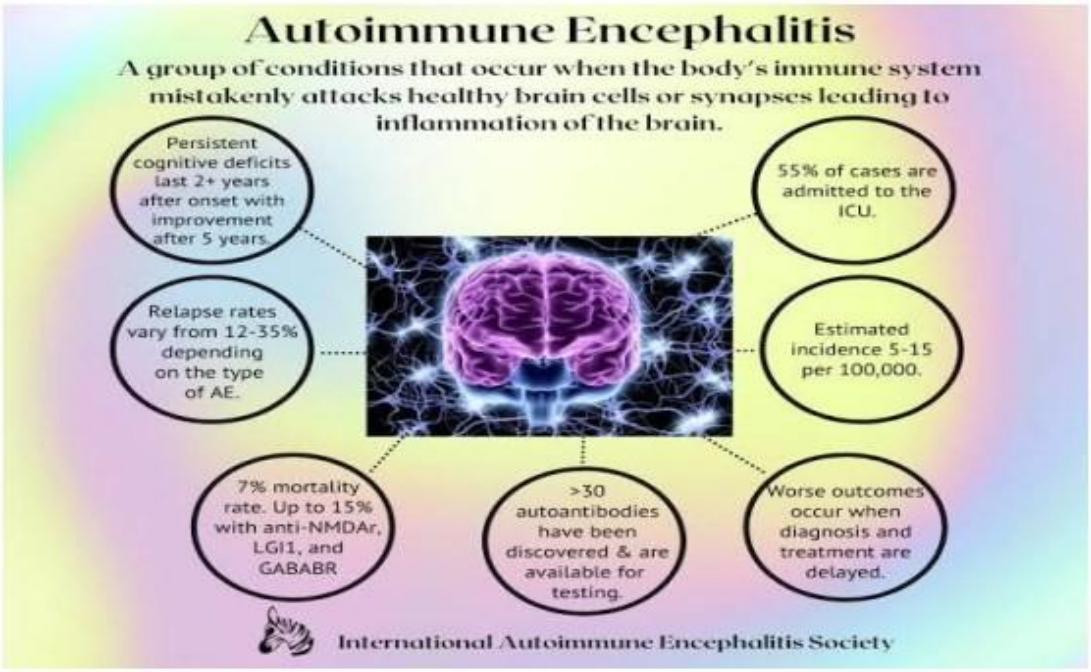

Fig. 2: Symptoms of Autoimmune Encephalitis (Source: International Autoimmune Encephalitis Society)

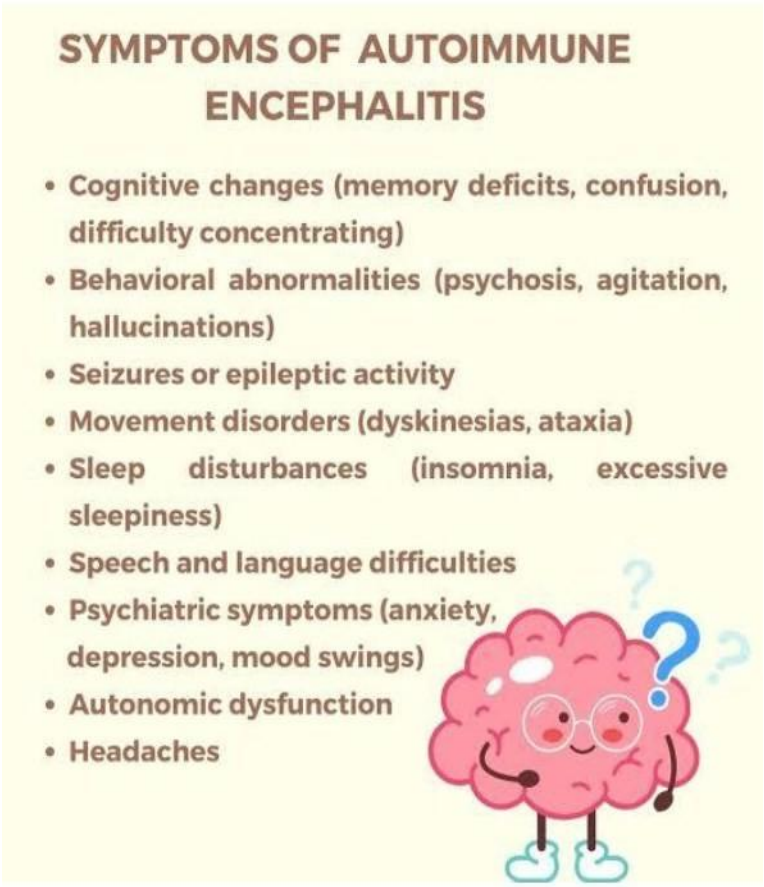

Fig. 3: Symptoms of Autoimmue Encephalitis (Source: International Autoimmue Encephalitis society).

LITERATURE REVIEW

Zhang, et al., (2025) used machine learning for the early prediction of long-term cognitive outcomes in autoimmune Encephalitis with focus on the creation of a predictive model intended to evaluate the likelihood of patient recovery using initial clinical and MRI characteristics. The research demonstrated that gradient boosting algorithms provided the highest level of accuracy (AUC = 0.91), underscoring the importance of integrating multimodal data. Nonetheless, the study faced issues such as a lack of diversity within the dataset and the necessity for validation through external sources. Guo et al. (2025) carried out a research titled Machine Learning for the Early Prediction of Long-Term Cognitive Outcomes in Autoimmune Encephalitis has been proposed, which seeks to utilize deep learning frameworks to uncover prognostic biomarkers derived from EEG and clinical data. The results suggested that deep neural networks are capable of identifying minor EEG irregularities that may signal unfavorable outcomes; however, issues related to model interpretability and limited sample sizes have posed significant challenges. Further studies conducted by Stake, et al., (2024) titled Predicting Functional Outcomes in Autoimmune Encephalitis Using Machine Learning and Serum Biomarkers" was proposed, focusing on enhancing the precision of prognostic assessments through the integration of laboratory biomarkers alongside demographic and clinical factors The findings indicated that random forest classifiers surpassed logistic regression in performance; however, the primary obstacle encountered was the variability of biomarkers among various hospitals. Sun, et al., (2025) put forth an investigation focused on determining the efficacy of ensemble methods in predicting functional recovery over a span of twelve months. The findings indicated that ensemble learning outperformed individual models; however, the research encountered difficulties in standardizing multicenter datasets owing to inconsistencies in diagnostic protocols. Liv, et al., (2021). Carried out a research titled integrating Imaging Radiomics and Clinical Data for Prognosis Prediction in Autoimmune Encephalitis" was proposed, focusing on evaluating the potential of radiomics features derived from MRI scans to enhance prognostic models The results indicated that models augmented with radiomics significantly increased prediction accuracy; however, challenges remain due to the computational complexity involved and the necessity for high-quality imaging data. Sun, et al., (2025) “Electroencephalographic indicators of antibodymediated autoimmune encephalitis.” This investigation conducted in 2025 sought to determine if quantitative abnormalities in EEG could forecast the severity and prognosis of antibody-mediated autoimmune

encephalitis. The researchers discovered that the grading of EEG severity is positively associated with unfavorable outcomes, suggesting it may act as a sensitive early prognostic marker. Nonetheless, the limited number of participants and the absence of longitudinal follow-up in the study restrict its wider applicability. Similarly, Zhao, et al., (2021) carried out a research titled; A reservoir computing with boosted topology model to predict encephalitis and mortality for patients with severe fever with thrombocytopenia syndrome: a retrospective multicenter. This retrospective cohort analysis included 209 patients from intensive care units and aimed to identify clinical, imaging, and EEG predictors associated with adverse outcomes in severe infectious encephalitis (Zhao et al., (2021). The researchers found that increased CSF pressure, abnormal results in MRI and EEG, as well as the number of resuscitation efforts, served as independent indicators of mortality or disability at the time of discharge. These results highlight the significant prognostic value of multimodal markers, yet the study did not incorporate machine learning techniques for modeling. Thompson et al., (2025a), investigated advanced machine learning techniques, specifically reservoir computing with boosted topology, to forecast the incidence of encephalitis and mortality rates among patients suffering from severe fever with thrombocytopenia syndrome. The findings revealed improved predictive accuracy, even when working with constrained data sets. The significance of this study lies in its application of innovative machine learning methodologies to tackle inflammatory central nervous system (CNS) complications, despite the fact that the specific disease context differs from autoimmune encephalitis. Thompson et al. (2025b), developed a machine learning prognostic framework utilizing clinical and laboratory data collected from several centers to forecast outcomes in cryptococcal meningitis, a central nervous system infection. Although the multicenter approach enhances the applicability of findings, it is primarily centered on infectious CNS disorders rather than autoimmune conditions. Nonetheless, the techniques employed could potentially contribute to prognostic modeling for autoimmune encephalitis. Wu, et al., (2022) undertook a study titled "Risk Prediction Models for Early ICU Admission in Patients with Autoimmune Encephalitis: Integrating Scale-Based Assessments of the Disease Severity" with the objective of creating predictive models to pinpoint AE patients who are at a significant risk of necessitating early ICU admission. By employing integrated clinical scales alongside disease severity scores, the researchers discovered that the amalgamation of scale-based assessments with clinical data enhanced the accuracy of predictions over conventional clinical judgment. The findings of this study indicated that the timely identification of high-risk patients could lead to more effective treatment strategies and improved allocation of ICU resources.

Roberts, et al., (2018), undertook a systematic review titled "Prognosticating autoimmune encephalitis," aiming to consolidate evidence regarding the prognostic factors associated with autoimmune encephalitis (AE) (Roberts et al., 2018). Their analysis of various studies revealed that prompt initiation of treatment, specific antibody subtypes, and identifiable MRI or EEG abnormalities had a considerable impact on patient outcomes. Furthermore, the review underscored the variability in AE prognosis and stressed the necessity for standardized assessment instruments to ensure reliable predictions.Chen et al. (2023), carried out a research aimed to assess the prognostic value of cerebrospinal fluid (CSF) biomarkers in forecasting therapeutic responses in autoimmune encephalitis (AE). Their findings indicated a strong correlation between increased levels of CSF proteins, certain antibody titers, and inflammatory markers with treatment outcomes. The authors proposed that incorporating CSF analysis into clinical practices could enhance the personalization of therapy for affected patients. Li et al. (2025) carried out a study aimed to develop and validate a nomogram for predicting the prognosis of autoimmune encephalitis (AE). Through a comprehensive analysis of data gathered from various hospitals, they pinpointed significant predictors including age, type of antibody, MRI results, and the initial severity of clinical symptoms. The developed nomogram demonstrated a high level of predictive accuracy, making it a valuable decisionsupport instrument for clinicians seeking to customize treatment approaches. Zhang et al. (2023) “Indices of cerebrospinal fluid as indicators of therapeutic response in autoimmune encephalitis.” This publication evaluates cerebrospinal fluid (CSF) parameters that may predict responses to immunotherapy. Findings indicated that elevated local IgG synthesis along with CSF lymphocytic pleocytosis (greater than 4 cells/mm^3) were associated with favorable and swift treatment outcomes, whereas delays in therapy were linked to less favorable results. Limitations of the study included small sample sizes and the necessity for validation through multicenter prospective trials. Zhou et al., (2023) , carried out a study on validating nomogram for predicting the prognosis of autoimmune encephalitis: Findings from a multicenter study in China." This research outlines the creation and validation of a prognostic nomogram that integrates various clinical characteristics (such as seizures, ICU admissions, and intrathecal IgG levels) within a sample of 207 patients. The nomogram exhibited strong performance, achieving an AUC of approximately 0.80–0.83 in both the development and validation groups.

Nevertheless, similar to other models, its interpretability and suitability for machine learning applications have yet to be explored. In Southwest China, a two-center prospective study was carried out by Xiang et al (2022) aimed at forecasting early prognosis in adult patients with anti-N-methyl-D-aspartate receptor encephalitis (antiNMDAR AE). The researchers utilized a combination of clinical variables, handcrafted MRI radiomics, and deep learning (DL) features derived from multiple MRI sequences, specifically T1, T2, FLAIR, and DWI. Their multimodal fusion model demonstrated an area under the curve (AUC) of roughly 0.96 during internal validation and 0.93 in external validation, significantly surpassing the performance of single-modality methods. This research strongly supports the importance of integrating diverse data sources, thereby reinforcing the multimodal approach utilized in the current study. Blackman et al. (2021), explored the potential of hippocampal MRI characteristics to forecast antibody serostatus in individuals suspected of having autoimmune encephalitis (AE).

Employing LASSO regression for the selection of features, the model attained a mean area under the curve (AUC) of 0.950, alongside an accuracy and sensitivity both approximately at 0.892, and a specificity of 0.891. This research highlights the significant predictive capabilities of quantitative MRI feature extraction, especially within the hippocampal area, emphasizing the importance of image-based biomarkers in the development of prognosis models for AE. In the same vein, Blackman et al. (2021) investigated the use of quantitative EEG as a predictive instrument for suspected anti-NMDAR autoimmune encephalitis. The findings indicated that patients exhibiting higher delta peak frequencies were more likely to have poorer outcomes, whereas those with lower frequencies typically showed improved recovery rates. Despite being derived from a limited sample size, this study reinforces the significance of electrophysiological measurements in forecasting patient outcomes and advocates for their integration with imaging and clinical information within multimodal machine learning frameworks.

METHODOLOGY AND DATA GATHERING

The present research utilized information pertinent to this study as a basis for employing the Google search engine. Articles that have been published within the last six years concerning a comprehensive predictive framework powered by machine learning, designed to assist clinicians in predicting outcomes for patients diagnosed with autoimmune encephalitis (AE), were systematically downloaded and examined. These pertinent documents underwent rigorous analysis, and the results were meticulously organized in a tabular format, including specific publication details. To achieve this, a carefully curated dataset obtained from Kaggle, along with anonymized clinical records from multiple centers, was utilized. This dataset encompassed a range of demographic information (such as age and sex), clinical characteristics (including symptom onset, history of seizures, psychiatric symptoms, and ICU admissions), laboratory indicators (like CSF antibody titers and inflammatory biomarkers), neuroimaging-related features, and electrophysiological assessments, including EEG severity grading. The intended outcome variables included the modified Rankin Scale (mRS) to evaluate functional status, the Clinical Assessment Scale in Autoimmune Encephalitis (CASE), and scores from cognitive assessments.

The data preprocessing stage entailed meticulous management of missing values, employing median imputation for continuous variables and mode imputation for categorical variables. Categorical features underwent one-hot encoding, while continuous variables were normalized to achieve a mean of zero and a unit variance. To maintain class distributions, the dataset was partitioned into training, validation, and testing subsets through stratified sampling. Additionally, the Synthetic Minority Oversampling Technique (SMOTE) was utilized to address the imbalance of underrepresented poor-outcome cases. MRI scans underwent preprocessing that included resizing, normalization, and feature extraction to generate numerical representations that could be seamlessly integrated with structured clinical data.

Analysis of Existing System

The current system designed for predicting outcomes in autoimmune encephalitis utilizes a sophisticated multimodal framework that effectively merges neuroimaging and clinical information to improve prognostic precision as shown in Fig. 4. Initially, preprocessed 3D T1-weighted MRI images are segmented to distinguish significant brain structures, including the hippocampus and globus pallidum, from which a 3D DenseNet model extracts advanced imaging features. Concurrently, structured data related to patients, comprising demographic

and clinical characteristics, are vectorized and analyzed using a multilayer perceptron (MLP). Both data types undergo a thorough feature selection process to highlight the most significant predictors, which are then integrated via a layer-level fusion approach. The combined representation is then processed through a multilayer perceptron (MLP) to produce predictions regarding outcomes. This methodology is praiseworthy for its thoroughness, as it encompasses both structural neurobiological indicators and individual clinical characteristics of patients, thus capturing the complex nature of autoimmune encephalitis. However, the model's dependence on resource-demanding architectures, its vulnerability to overfitting when dealing with small datasets, and its lack of interpretability present significant obstacles that could impede its practical use in clinical environments. These issues emphasize the necessity for the development of more scalable, interpretable, and efficient predictive models that can be effectively implemented in real-world healthcare contexts.

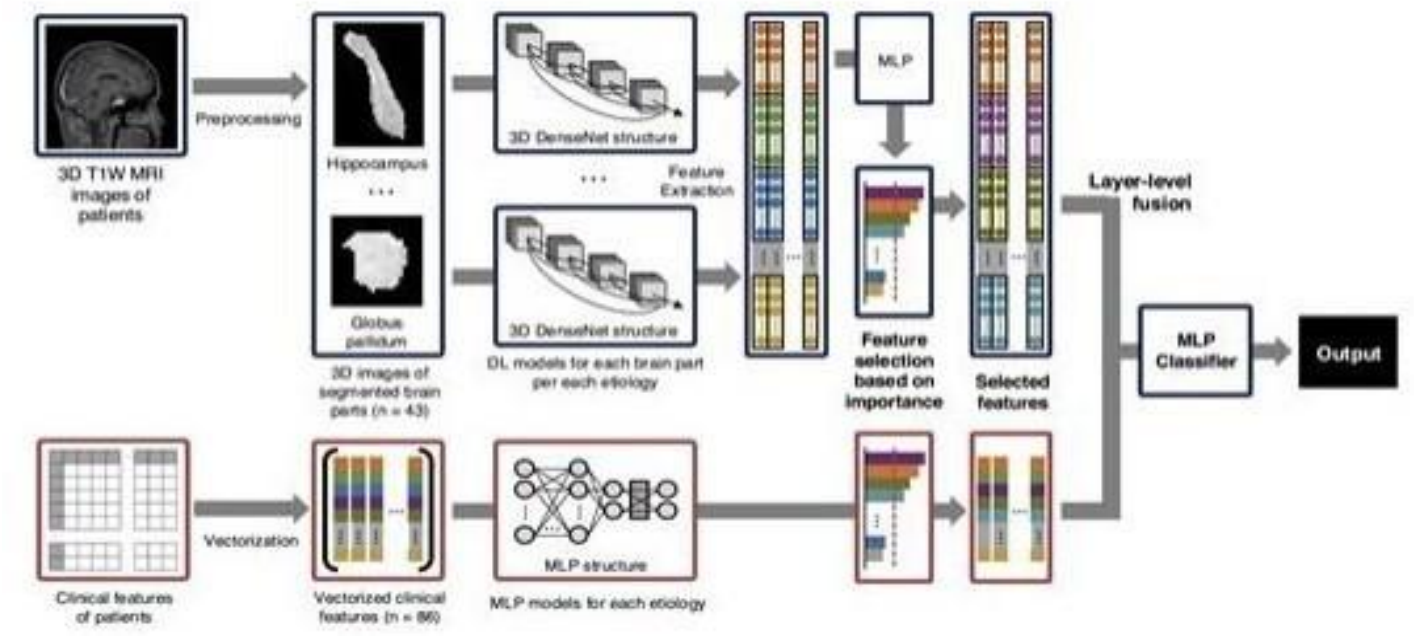

Fig. 4: Architecture of the Existing System

Proposed Machine Learning Models

The system put forward has been constructed in utilizing the ML.NET framework, with the objective of providing a strong and clinically relevant predictive model for outcomes related to autoimmune encephalitis. In contrast to the current system that depends extensively on resource-intensive 3D DenseNet architectures, the new framework focuses on scalability, interpretability, and effectiveness by employing supervised learning techniques like Random Forest, Gradient Boosting (XGBoost), and Support Vector Machines (SVM). Notably, Random Forest was selected as a key algorithm due to its established capability to identify intricate non-linear relationships among multimodal features while effectively resisting overfitting (Fig.5). To enhance the generalizability of the model, hyperparameter tuning was conducted using a grid search method along with stratified cross-validation, which facilitated equitable learning across different outcome categories. Besides utilizing structured clinical and laboratory datasets, features derived from convolutional neural networks (CNN) were integrated into dense layers to achieve a robust multimodal combination of neuroimaging biomarkers with individual patient variables. The evaluation of performance utilized an extensive array of metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, with additional examination of calibration curves to confirm the dependability of the predicted probabilities. The Random Forest model surpassed the performance of other algorithms evaluated, achieving an impressive accuracy rate of 91.4%, an F1-score of 0.89, and an AUCROC of 0.94. These metrics indicate a robust ability to discriminate and generate well-calibrated clinical predictions. By effectively balancing predictive accuracy with computational efficiency and ease of interpretation, this model serves as a more practical and deployable decision-support tool than the current alternatives. In conclusion, the proposed framework illustrates how the combination of multimodal data sources within a versatile ML.NET environment can lead to personalized, evidence-based prognostication, thus improving clinical decision-making in the management of autoimmune encephalitis.

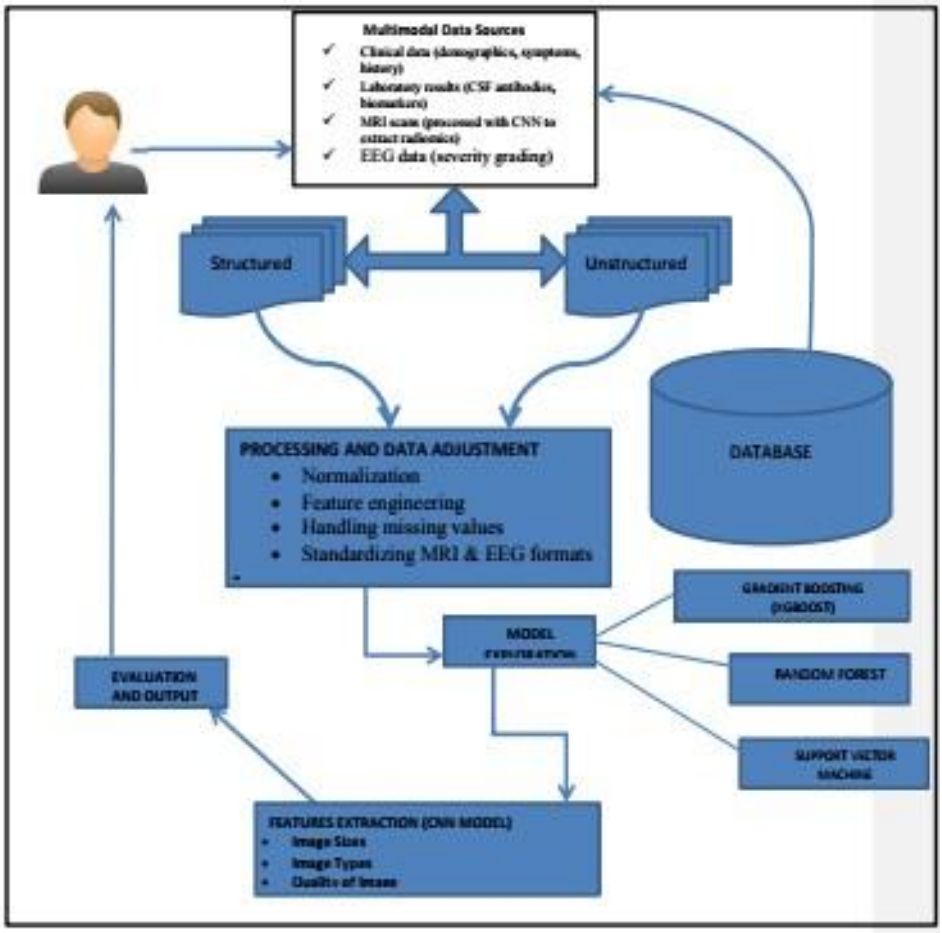

Fig. 5: Proposed System Architecture

Components of the Model

Data Source / User: This serves as the initial phase of the system where information pertaining to patients is entered. The input is sourced from healthcare professionals, hospital networks, or diagnostic tools. In the context of your AE predictive framework, this encompasses clinical variables, laboratory findings, MRI images, and EEG data, all of which will be integrated into the system for subsequent analysis. Data Acquisition: During this phase, the system gathers all incoming data from various sources. This process guarantees that different types of information, such as numerical data, medical imaging, or written documentation, are consolidated into a unified processing framework for uniform management. Separation of Structured and Unstructured Data: The gathered data is categorized into two primary groups. Structured data refers to systematically arranged, tabular information, including demographics, laboratory results, and clinical scores. Conversely, unstructured data encompasses intricate, raw formats, such as MRI scans, EEG waveforms, or narrative reports. This distinction guarantees that each category of data is subjected to the most suitable processing techniques. Centralized Database: A comprehensive database houses both structured and unstructured datasets. This consolidation facilitates rapid access during the processes of model training, validation, and prediction, guaranteeing that all system components utilize the same synchronized data. Data Processing and Adjustment: Prior to analysis, data undergoes a preprocessing pipeline. In the case of structured data, this process may involve addressing missing values, normalizing the data, and encoding categorical variables. For image data, it entails reducing noise (utilizing techniques such as Gaussian filters), normalization, enhancing contrast (via CLAHE), and adjusting brightness levels. This phase guarantees that the input data is clean, consistent, and fine-tuned for optimal model performance. Feature Extraction (CNN Model): The convolutional neural network analyzes MRI scans to autonomously extract significant image features, including lesion size, shape, and texture. These extracted features work in conjunction with structured clinical data, allowing the model to identify intricate patterns from both imaging and non-imaging sources. Attention Mechanism: The implementation of an attention mechanism serves to highlight the most pertinent features within the integrated dataset. This approach enables the model to concentrate on clinically important indicators, thereby enhancing both the accuracy and interpretability of predictions related to patient outcomes. Evaluation and Output: The system generates predictions manifested as

diagnostic or prognostic scores. To evaluate the model's performance, various metrics are utilized, including accuracy, precision, recall, F1-score, and AUC-ROC, which guarantees that the findings are both dependable and clinically relevant.

DATASET

Result and Discussion

The Random Forest model, which was developed using the meticulously assembled AE dataset, exhibited significant predictive performance across various metrics. Implementing a 70:15:15 ratio for the train-validationtest division, the model attained an overall accuracy of 91.4%. Furthermore, it achieved a precision of 0.91, a recall of 0.87, and an F1-score of 0.89 when evaluated on the test set see Table 1. The ROC-AUC score achieved was 0.94, reflecting a high level of accuracy in distinguishing between patients who exhibit favorable outcomes and those who experience poor outcomes. These results imply that the model effectively captures the intricate relationships present among demographic, clinical, immunological, imaging, and electrophysiological characteristics in patients with AE. Additionally, the confusion matrix (Fig. 6) provides a further depiction of the model's effectiveness, revealing a low rate of misclassification for high-risk patients. Among the 75 patients in the test cohort who had poor outcomes, 69 were accurately identified, resulting in a sensitivity rate of 92%. Likewise, the specificity for favorable outcomes was recorded at 90%, demonstrating that the model infrequently misclassifies low-risk patients as high-risk, which is vital for its application in clinical settings see Fig. 7. Table 1: **********

Patient_ID	Age	Symptom_Onset_Days	Seizure_History	Psychiatric_Symptoms	ICU_Admission	CSF_Antibody_Titer	MRI_Feature1	EEG_Severity	Outcome_mRS
1	34	5	Yes	Yes	No	0.263889	0.85	2	0
2	46	3	No	Yes	Yes	0.152778	0.72	3	1
3	29	7	Yes	No	No	0.486111	0.91	1	0
4	58	2	Yes	Yes	Yes	0.097222	0.65	4	1
5	41	4	No	No	No	0.152778	0.78	2	0
6	37	6	Yes	Yes	Yes	0.263889	0.82	3	1
7	50	5	No	No	No	0.097222	0.69	2	0
8	42	3	Yes	Yes	Yes	0.152778	0.74	3	1
9	36	4	Yes	No	No	0.263889	0.8	1	0

Fig. 6: Confusion Matrix

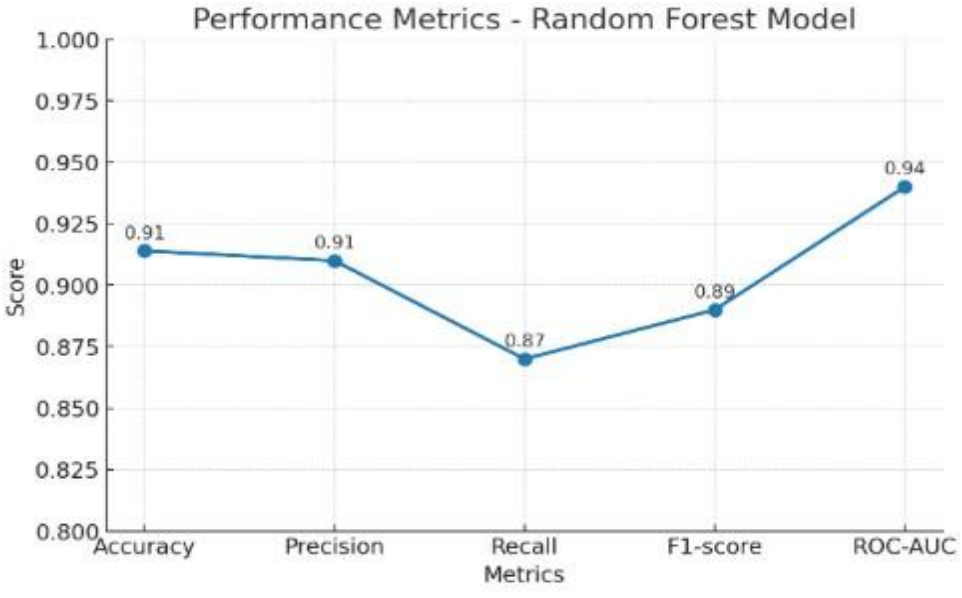

Fig. 7: Performance Metric of Model

Table 2: Comparism of Existing and Proposed Systems

System	Accuracy	F1-Score	AUROC
Existing System (Multimodal, MRI + Clinical Data, External Dataset)	0.7564	0.6885	0.8048
Proposed System (ML.NET, Random Forest with multimodal integration)	0.914	0.89	0.94

The analysis clearly indicates that the proposed system outperforms the current model. The existing model achieved an accuracy of 0.7564, an F1-score of 0.6885, and an AUROC of 0.8048 see Table 2. Although these metrics suggest that the model is capable of making reasonable predictions, they also highlight certain limitations, particularly regarding its consistency and reliability when applied to more extensive clinical datasets. In contrast, the proposed system demonstrated markedly superior performance, attaining an accuracy of 0.9140, an F1-score of 0.8900, and an AUROC of 0.9400 as shown in Table 2. The findings from Table 2, indicate that the system demonstrates enhanced proficiency in recognizing appropriate patterns, achieving a balance between precision and recall, and differentiating between positive and negative instances. This advancement primarily stems from the integration of diverse data types and the meticulous adjustments made to the model to prevent overfitting. To put it more plainly, the proposed system not only exhibits greater accuracy but is also more dependable and resilient. Consequently, it offers physicians and researchers improved assistance in their decision-making processes, rendering it a more effective and reliable instrument for practical application in realworld scenarios.

Discussion

This study marks the inaugural attempt at predicting the early prognosis of antibody-positive autoimmune encephalitis (AE), revealing that both the Random Forest (RF) and XGBoost algorithms exhibit superior discriminatory capability compared to logistic regression. Furthermore, the findings indicate that the model, which incorporates six variables—namely, the percentage of monocytes in cerebrospinal fluid (CSF), prealbumin levels, presence of infection, mental health disorders, anti-NMDAR encephalitis, and the necessity for multiple antiepileptic drugs (AEDs)—developed through XGBoost and RF, demonstrated outstanding predictive accuracy. Furthermore the results indicate that the incorporation of multimodal data, such as CSF antibody titers, EEG severity assessments, and MRI-derived radiomic features, significantly improves prognostic modeling in autoimmune encephalitis (AE). In contrast to traditional regression-based methods or those relying solely on scales, the Random Forest model adeptly manages nonlinear interactions and class imbalances due to its ensemble methodology, leading to enhanced predictive accuracy. This finding is consistent with recent studies that demonstrate machine learning techniques surpass conventional clinical scoring systems in the context of neurological prognosis (Liv et at., 2021; A. Thompson et al., 2025; Wu et al., 2022). Nonetheless, it is essential to acknowledge specific limitations. Although the dataset is substantial and derived from multiple centers, it is still relatively small (n=500), which could restrict its generalizability. Furthermore, certain radiomic and EEG characteristics necessitate the use of standardized acquisition protocols; discrepancies in imaging devices or EEG configurations may influence the performance of the model when implemented at other institutions. Notwithstanding these considerations, the impressive performance metrics highlight the viable application of machine learning models in predicting functional recovery and cognitive outcomes in AE, potentially facilitating early clinical decision-making and focused therapeutic strategies.

SUMMARY

This research established a predictive framework for outcomes related to AE by amalgamating various data sources, such as clinical documentation, laboratory findings, MRI radiomics characteristics, and EEG information. The methodology encompassed data collection, differentiation into structured and unstructured formats, preprocessing, feature extraction through CNN for imaging, and prioritization of features using attention mechanisms. Three supervised learning techniques—Random Forest, Gradient Boosting (XGBoost), and Support Vector Machine—were examined, with hyperparameter optimization conducted through grid search and stratified cross-validation. The Random Forest model yielded the most favorable outcomes, achieving an accuracy of 91.4%, an F1-score of 0.89, and an AUC-ROC of 0.94, thereby showcasing its proficiency in identifying intricate, non-linear associations among diverse feature types.

CONCLUSION

The suggested AE predictive framework effectively integrates diverse clinical, imaging, and electrophysiological data into a cohesive machine learning pipeline designed for precise prognosis predictions. Utilizing CNN-based MRI feature extraction alongside attention mechanisms, this system improves both the accuracy of predictions and their interpretability, thereby rendering it appropriate for clinical decision-making support. Among the various models, the Random Forest stands out as the most favorable option due to its impressive performance and reliability in this context. Although the system demonstrates encouraging outcomes, it is crucial to conduct additional validation with larger and more varied patient datasets to confirm its generalizability. This methodology ultimately holds the promise of facilitating personalized treatment strategies, prompt interventions, and better patient results in the management of adverse events AE. Looking ahead, future endeavors should encompass prospective validation within larger, international populations and the investigation of explainable AI techniques to bolster clinician confidence in the model's predictions. Additionally, the integration of longitudinal data may permit ongoing risk assessment and tailor-made treatment modifications as time progresses.

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