A Multi-modality-based Multiple Sclerosis Detection Model

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ABSTRACT

This study proposes a novel method for detecting multiple sclerosis (MS) by integrating multi-modality data fusion techniques. Leveraging the complementary information from both health records and magnetic resonance imaging (MRI), our approach aims to enhance the accuracy and reliability of MS detection. We utilized DenseNet 201 to extract features from MRI scans, exploiting its capability to capture intricate patterns in brain images associated with MS pathology. Additionally, we employed bidirectional long short-term memory networks to extract temporal patterns from health records, capturing longitudinal patient data crucial for understanding disease progression. A feature fusion technique was then applied to integrate the extracted features from MRI and health records, combining the spatial information from imaging data with the temporal dynamics captured in health records. Finally, a multi-layer perceptron was employed to perform the final prediction task based on the fused features. The proposed model was experimented with in the Kaggle datasets, covering 271 individuals. Remarkably, our proposed model achieved an impressive accuracy of 99.2% in MS detection, highlighting its effectiveness in leveraging multi-modality data for diagnostic purposes. By combining information from both MRI scans and health records, our approach offers a comprehensive and holistic understanding of the disease, enabling more accurate and timely diagnosis. Additionally, further validation studies in clinical settings are warranted to assess our approach’s real-world utility and clinical impact in improving patient outcomes and facilitating better management of MS.

KEYWORDS

multiple sclerosis, multi-modality data, Bi-LSTM, feature fusion, multi-layer perceptron, transfer learning

INTRODUCTION

Multiple sclerosis (MS) is a complex autoimmune disease characterized by inflammation, demyelination, and neurodegeneration within the central nervous system (Zeng et al., 2020). It affects millions of individuals worldwide, with significant variability in clinical presentation, disease course, and progression (Brosch et al., 2016; Sah and Direkoglu, 2022). The etiology of MS remains incompletely understood, although it is widely believed to result from a combination of genetic predisposition, environmental factors, and dysregulated immune responses. Clinically, MS manifests with a myriad of neurological symptoms, including sensory disturbances, motor deficits, cognitive impairment, and fatigue, leading to substantial disability and impaired quality of life for affected individuals (Shoeibi et al., 2021).

MS-related fatigue is a prevalent and incapacitating symptom that affects as many as 80% of people (Shoeibi et al., 2021). It may greatly impair an individual’s capacity to do everyday tasks and negatively impact their overall quality of life. MS may manifest various motor symptoms such as muscle weakness, stiffness, tremors, and challenges in coordinating movements and maintaining balance (Aslam et al., 2022). These symptoms might affect the ability to move and engage in physical activity. People with MS may have sensory disruptions, including numbness, tingling, pain, and changes in feeling, which may affect different areas of the body (Moazami et al., 2021). Optic neuritis, which is the inflammation of the optic nerve, is a frequently occurring first sign of MS. It results in visual impairments such as blurry vision, seeing double,
and reduced visual sharpness. MS may have significant emotional and psychological consequences, such as sadness, anxiety, fluctuations in state of mind, and alterations in personality (Sepahvand et al., 2020). The unexpected nature of the condition and its influence on everyday living might worsen these symptoms.

Background

The diagnosis of MS traditionally relies on a combination of clinical evaluation, neuroimaging, and laboratory investigations (Yoo et al., 2019; Kim et al., 2020; Sepahvand et al., 2020). Among these modalities, magnetic resonance imaging (MRI) has emerged as a cornerstone in diagnosing and managing MS. MRI findings in MS typically include the presence of focal lesions, characterized by areas of hyperintensity on T2-weighted and fluid-attenuated inversion recovery sequences, reflecting inflammatory demyelination and axonal injury. Additionally, advanced MRI techniques, such as diffusion-weighted imaging, magnetization transfer imaging, and spectroscopy, provide valuable insights into microstructural alterations, tissue integrity, and metabolic changes associated with MS pathology (Roca et al., 2020).

Despite the diagnostic utility of MRI in MS, the manual interpretation of MRI scans is labor-intensive, time-consuming, and subject to inter-observer variability, particularly in detecting and characterizing subtle or early disease-related changes (Ma et al., 2022). Moreover, the increasing prevalence of MS and the growing demand for neuroimaging services underscore the need for more efficient and accurate methods for MS diagnosis and monitoring (Mortazavi et al., 2012).

Motivation

There is increasing interest in developing automated approaches for MS identification utilizing machine learning (ML) and deep learning (DL) techniques, driven by the difficulties mentioned above and the promise of artificial intelligence to change medical imaging and disease diagnosis. Automated MS detection systems have the potential to improve diagnosis accuracy, optimize workflow, and enable early intervention in MS patients by using abundant data from MRI scans and harnessing the computational capabilities of neural networks.

Contribution

The primary contribution of this research is developing and assessing an innovative DL method for automatically detecting MS using MRI data. The proposed study involves a thorough pipeline that combines sophisticated DL models, bidirectional long short-term memory (Bi-LSTM) and DenseNet 201, to extract features from MRI images. These features can identify subtle and intricate patterns that indicate MS disease. Afterward, a multi-layer perceptron (MLP) model is trained using the collected characteristics to distinguish between normal and abnormal MRI data, allowing for automated diagnosis of MS.

Our work provides significant advancements to the profession in several ways.

- **Advanced feature extraction**: To improve the automated MS detection system's ability to identify and quantify unique patterns associated with MS, our technique uses state-of-the-art DL architectures for feature extraction. This boosts the system's discriminative power and resilience.
- **Model evaluation and optimization**: In order to minimize overfitting and generalization error and increase classification performance, we carefully evaluate and fine-tune the MLP model parameters. The effectiveness of the suggested model is thoroughly assessed on a varied MRI dataset obtained from the Kaggle repository, guaranteeing its dependability and applicability to various patient demographics and imaging techniques.
- **Clinical translation and impact**: Our research highlights the potential benefits of automated MS detection systems in improving patient outcomes, speeding up patient treatment, and increasing diagnosis accuracy for MS patients. Through the automation of the detection process, our model shows potential for aiding in the early diagnosis, tailored treatment planning, and monitoring of disease progression in patients with MS. This eventually leads to enhanced clinical management and better patient results.

The use of multiple modalities in the proposed MS detection model significantly enhances the diagnostic process by providing a more comprehensive understanding of the disease through the integration of diverse types of data. Combining MRI scans and health records allows the model to leverage the strengths of both data types. MRI scans provide detailed spatial information about brain structures, helping to identify physical abnormalities such as lesions and atrophy associated with MS. Meanwhile, health records offer longitudinal data that track patient symptoms, treatment responses, and disease progression over time.

The study offers a comprehensive understanding of MS. Traditional diagnostic methods often fall short in capturing the full spectrum of the disease, particularly its progression and variability in symptoms over time. By integrating data from multiple sources, the model provides a holistic view of MS, encompassing its structural and temporal aspects. This comprehensive approach improves diagnostic precision and enhances the understanding of the disease’s progression and patient-specific characteristics.

The remaining part of this study is organized as follows: the Literature Review section presents the existing MS detection approaches. The proposed methodology is outlined in the Research Methodology section. The Results and Discussion section reveals the findings of the experimental analysis. Finally, the study contribution and future direction of this study are highlighted in the Conclusions section.
LITERATURE REVIEW

DL, an ML that uses artificial neural networks with numerous layers to extract hierarchical representations from data, has become a potent approach for automated MS identification and characterization (Gulay et al., 2022). Convolutional neural networks, a kind of DL model, have shown exceptional performance in various medical imaging tasks, such as segmenting lesions in MS, classifying disease subtypes, and predicting therapy response (Salem et al., 2019). Nevertheless, most current DL methods for MS detection concentrate on segmenting lesions or classifying patients as either MS or non-MS, disregarding the many characteristics of MS and the potential value of catching subtle disease-related alterations beyond the extent of lesions.

There has been an increasing interest in applying ML and DL approaches to automatically diagnose and classify MS using MRI data (Ghosal et al., 2019; de Oliveira et al., 2022). Multiple research studies have investigated ML methods, such as support vector machines, random forests, and neural networks, to automatically segment and classify MS lesions on MRI images (Narayana et al., 2020; Coronado et al., 2021; Gaj et al., 2021; Acar et al., 2022; Alessandro et al., 2022; La Rosa et al., 2022; Coll et al., 2023). These techniques have shown promising outcomes in accuracy, sensitivity, and specificity, providing prospective advantages in terms of efficiency and consistency when compared to the manual interpretation conducted by radiologists.

Although there have been advancements in MRI and ML to detect MS automatically, there is still a lack of understanding in creating advanced DL models that can accurately identify intricate and complex patterns associated with MS pathology, going beyond the typical features found in lesions. Current methods often depend only on lesion segmentation or overlook the many presentations of MS on MRI, such as widespread tissue abnormalities, shrinkage, and microscopic structural alterations. Furthermore, there is a scarcity of research investigating the applicability and practical implementation of automated MS detection systems, especially in real-world clinical environments that include a wide range of patients and imaging procedures.

This work aims to address the knowledge gap by introducing a new and innovative method that automatically uses DL to diagnose MS using MRI data. Our technique utilizes robust DL architectures to extract features and optimize models. The goal is to detect various anomalies associated with MS and enable precise and dependable diagnosis of MS in multiple patient groups and MRI datasets. Additionally, our research adds to the broader domain of artificial intelligence in medicine by showcasing the clinical significance and possible influence of DL-powered automated MS detection systems in strengthening the precision of diagnosis, simplifying the process, and improving patient care in MS diagnosis.

RESEARCH METHODOLOGY

Figure 1 shows the recommended method to detect MS using the multi-modality data. MRI scans provide detailed spatial information about brain structures, enabling the detection of lesions, atrophy, and other anatomical changes associated with MS. These scans are crucial for identifying the physical manifestations of the disease. However, MRIs alone may not fully capture the temporal progression and clinical symptoms experienced by patients over time. Health records, on the other hand, offer longitudinal data that include patient histories, symptom progression, treatment responses, and other relevant clinical information. These temporal data are vital for understanding how the disease evolves, how patients respond to therapies, and how symptoms fluctuate, which are aspects that static imaging cannot capture. By incorporating health records, the model gains access to this dynamic and patient-specific information, enriching the diagnostic process. The authors integrated DenseNet 201 and Bi-LSTM models’ features in this study using a feature fusion technique. These models generate a diverse set of features associated with MS. The feature fusion technique was employed to identify unique features. In addition, an MLP technique was used to classify the extracted features into normal and abnormal classes.

The Kaggle MS dataset (Kaggle, 2023a,b) is an openly accessible repository of MRI scans and accompanying clinical information designed for MS diagnosis and treatment research. This dataset is an excellent resource for developing and evaluating ML and DL algorithms for the automated identification, segmentation, and classification of anomalies associated with MS on MRI images.
The use of DenseNet 201 for feature extraction has been extensively employed in diverse computer vision tasks, including image classification, object recognition, semantic segmentation, and medical image analysis. Because of its high performance and effective feature representation skills, DenseNet 201 is often used as a feature extractor in transfer learning situations. In these settings, pretrained models are adjusted on domain-specific datasets to obtain cutting-edge performance with a small amount of training data. The feature extraction process in DenseNet 201 comprises the systematic combination and improvement of features inside dense blocks, aided by dense connectivity and transition layers. DenseNet 201 utilizes dense connection and feature reuse to extract intricate and layered representations of input pictures, making it very effective for various computer vision applications. DenseNet is distinguished by its dense connection design, which allows for the reuse of features and promotes the flow of gradients throughout the network. DenseNet 201 differs from standard feed-forward topologies by establishing connections between each layer and every other layer inside the same dense block rather than connecting them sequentially. The high level of interconnectivity in this network architecture promotes the reuse of features, facilitates the propagation of features, and mitigates the vanishing gradient issue, resulting in effective training and enhanced model performance.

During feature extraction, input pictures are processed through the stem block to extract basic features, which are then gradually combined and improved inside the dense blocks. In each compact cluster, feature maps are intricately linked, enabling the seamless transmission of information from initial layers to subsequent levels without any deterioration. The high level of interconnectivity in the network facilitates the reuse of features and motivates the network to acquire comprehensive and hierarchical representations of input pictures. Transition layers are strategically placed between dense blocks in order to regulate the expansion of feature maps and enable spatial downsizing. This ensures that the network maintains an optimal balance between its ability to represent information and its computing efficiency.

DenseNet 201 provides efficient feature extraction due to its dense connectivity pattern, where each layer receives direct input from all previous layers. This architecture mitigates the vanishing gradient problem and allows for more effective learning, even with deeper networks. DenseNet 201 also requires fewer parameters compared to other deep convolutional networks like ResNet or very deep convolutional networks, thanks to its feature reuse mechanism. This makes it more computationally efficient while maintaining high performance, which is crucial when processing large MRI datasets. Additionally, the direct connections between layers facilitate better gradient flow during training, leading to more effective learning and convergence. DenseNet 201’s ability to capture detailed spatial information from MRI scans makes it well-suited for detecting structural abnormalities associated with MS, contributing to more accurate and reliable diagnoses.

DenseNet 201 is frequently trained using supervised learning methods, in which input pictures are matched with their associated ground truth labels. During training, the neural network can reduce a predetermined loss function, such as cross-entropy loss, by modifying its parameters using Adam’s optimization methods. Following the training process, the acquired features may be subsequently optimized for particular tasks such as image classification or object recognition. The authors froze the initial layers and retrained the remaining layers to extract the intricate patterns.

Using Bi-LSTM networks for health record feature extraction in MS detection represents a novel approach with significant potential benefits. Bi-LSTM networks are well-suited for capturing temporal dependencies in sequential data, making them particularly effective for analyzing longitudinal health records, which often contain diverse and time-varying information about a patient’s medical history, symptoms, and disease progression. In the context of MS detection, Bi-LSTM networks can extract relevant patterns and trends from patients’ health records over time, capturing subtle changes and trajectories associated with the disease. For instance, they can identify patterns of symptom onset, progression, remission, and relapse, as well as variations in treatment response and disease activity. By analyzing these temporal patterns, Bi-LSTM networks can uncover valuable insights into the disease course and help discriminate between MS and other neurological conditions.

Furthermore, Bi-LSTM networks can learn representations from raw sequential data, eliminating the need for manual feature engineering and allowing for a more data-driven approach. This enables the model to adapt to diverse and heterogeneous health record formats, accommodating data structure and quality variations across healthcare systems.

The Bi-LSTM model is uniquely suited to capture these temporal dynamics because it can simultaneously consider past and future contexts, unlike traditional models that only process data in one direction. This bidirectional capability enables the model to understand complex temporal patterns and dependencies, enhancing its ability to extract meaningful insights from health records. By leveraging the Bi-LSTM model, the study can effectively integrate temporal information with spatial data from MRI scans, providing a more comprehensive and accurate diagnosis of MS. Thus, the inclusion of the Bi-LSTM model is essential for capturing the intricate and evolving nature of MS as reflected in patients’ longitudinal health data.

Bi-LSTM networks are designed to capture temporal dependencies in sequential data, processing information in both forward and backward directions. This bidirectional approach allows Bi-LSTMs to understand the context of each data point more comprehensively, which is particularly important for health records that reflect the progression of MS over time. Bi-LSTMs excel at learning long-term dependencies, providing a more holistic view of patient health records. This is crucial for understanding the progression of chronic diseases like MS, where long-term patterns in the data are important. The bidirectional nature of Bi-LSTMs enhances the model’s ability to consider both past and future information simultaneously, leading to a better understanding of the temporal dynamics in health records and more accurate predictions of disease progression and patient outcomes.
Incorporating Bi-LSTM networks for health record feature extraction in MS detection offers several advantages, including capturing temporal dynamics, learning from raw sequential data, and adapting to diverse data sources. This approach holds promise for improving the accuracy and reliability of MS diagnosis by leveraging longitudinal patient information and complementing other modalities such as imaging data. Further research and validation in clinical settings are needed to assess the full potential of Bi-LSTM-based health record analysis for MS detection and its integration into clinical practice.

Once the spatial features functional MRI (FMRI) and temporal features fast hemodynamic response (FHR) are extracted, the next step is to combine them into a single, unified feature vector through concatenation. Concatenation involves appending the feature vector from one modality to the end of the feature vector from the other modality. This operation creates a new feature vector that integrates both spatial and temporal information.

Mathematically, if \( F_{\text{MRI}} \) is of dimension \( d_{\text{MRI}} \) and \( F_{\text{HR}} \) is of dimension \( d_{\text{HR}} \), the concatenated feature vector \( F_{\text{concat}} \) will have a dimension of \( d_{\text{MRI}} + d_{\text{HR}} \).

The concatenation can be expressed as follows: 
\[
F_{\text{concat}} = [F_{\text{MRI}} \; F_{\text{HR}}].
\]

This concatenated vector \( F_{\text{concat}} \) effectively combines the rich spatial information from the MRI scans with the detailed temporal information from the health records.

The MLP architecture is built using input dimensions that match to the dimensionality of the retrieved features. It usually has many densely linked layers with nonlinear activation functions like rectified linear unit. Figure 2 shows the recommended MLP architecture for MS identification. Dropout layers are included between the dense layers to regularize the network and mitigate overfitting. Dropout regularization is a technique that randomly removes a portion of neurons during the training process. This compels the network to acquire more resilient and comprehensive representations. This technique mitigates overfitting by diminishing the network’s dependence on individual neurons and promoting more evenly distributed feature representations. Early stopping is a strategy used to avoid overfitting by continuously evaluating the model’s performance on a separate validation set while it is being trained. The training process is stopped when the validation loss begins to rise, or the accuracy starts to decline, suggesting that the model is starting to overfit the training data. The MLP is built and then trained on the training data using a binary cross-entropy loss function, Bayesian optimization, and Hyperband optimization. During training, dropout is used as a means of regularization for the network. The validation set supervises the training process, and training concludes when the early stopping requirements are satisfied. After training completion, the trained model’s performance is assessed on a separate test set to determine its capacity to generalize. Performance evaluation of the model in differentiating normal and pathological MRI images may be measured using measures such as accuracy, precision, recall, F1-score, and the area under regional operating characteristic (AUROC) and precision-recall curve (AUPRC).

### RESULTS AND DISCUSSION

The study was implemented using Red Hat Extensive Linux 8.5, Kernel version 4.18.0-348, Intel i7, 16 GB RAM (Red Hat Enterprise Linux, Fedora Linux, USA), and NVIDIA 350X (NVIDIA, USA). The Kaggle MS dataset was divided into a training set (70%), a validation set (15%), and a test set (15%). The authors used dropout regularization and early stopping strategies to improve the model’s performance. A total of 156 epochs were used to train the model. Figure 3 shows the model’s performance during each epoch.

Table 1 reveals the individual performance of the proposed model. The experimental results obtained from the proposed model, trained and evaluated using the Kaggle MS dataset, underscore its remarkable performance in the task of MS detection. With an average accuracy of 99.4% and a specificity of 98.8%, the model demonstrates a high level of efficacy in distinguishing between normal and abnormal MRI scans indicative of MS pathology. This exceptional level of accuracy suggests that the model can reliably identify MS-related abnormalities with a minimal rate of false positives, thereby minimizing the risk of misdiagnosis and ensuring high diagnostic confidence.

The observed specificity of 98.8% is particularly noteworthy, as it reflects the model’s ability to correctly identify actual negative cases (i.e. individuals without MS) with high accuracy. This high specificity is essential in clinical practice to minimize the likelihood of false alarms or unnecessary interventions, thereby reducing patient anxiety and healthcare costs associated with follow-up testing or unnecessary treatments.

The superior performance of the proposed model can be attributed to several factors. First, using advanced feature extraction techniques such as DenseNet 201 or EfficientNet B7 enables the extraction of discriminative features from MRI scans, capturing subtle patterns indicative of MS pathology. These pretrained models leverage DL architectures optimized for image analysis tasks, allowing the model to learn rich and informative representations of MS-related abnormalities.

**Figure 2:** MLP-based MS detection. Abbreviations: MLP, multi-layer perceptron; MS, multiple sclerosis.
Moreover, dropout regularization within the MLP architecture enhances the model’s generalization capability by preventing overfitting and encouraging learning more robust and generalized feature representations. Dropout serves as a regularization mechanism that reduces the model’s reliance on specific neurons, promoting feature diversity and reducing the risk of memorizing training data. Figure 3 shows the findings of the performance analysis.

Table 2 highlights the comparative analysis outcomes. The proposed model achieves substantially higher performance metrics compared to baseline models. With an average accuracy of 99.4% and a specificity of 98.8%, the proposed model surpasses the baseline models in accurately distinguishing between normal and abnormal MRI scans indicative of MS pathology. This superior performance indicates the model’s effectiveness in capturing and leveraging discriminative features extracted from MRI images.

Unlike baseline models that may struggle with overfitting or lack the capacity to generalize well to unseen data, the proposed model incorporates dropout regularization and early stopping strategy, enabling it to generalize more effectively. The proposed model demonstrates superior generalization capability by mitigating overfitting and promoting robust feature learning, thereby enhancing its reliability and applicability in real-world scenarios.

The proposed model leverages state-of-the-art feature extraction techniques such as DenseNet 201 or EfficientNet B7, which are trained on large-scale image datasets. These techniques enable the model to extract rich and informative representations of MS-related abnormalities from MRI scans, capturing subtle patterns indicative of MS pathology. In contrast, baseline models may rely on handcrafted features or simplistic feature extraction methods, limiting their capacity to capture complex and nuanced patterns. Figure 4 presents the outcomes of the comparative analysis.

Table 3 presents the outcomes of the reliability analysis. The high AUROC and AUPRC signifies its ability to minimize the occurrence of false positives, i.e., misclassifying regular MRI scans as abnormal. This is crucial in clinical practice to avoid unnecessary interventions, reduce patient...
anxiety, and minimize healthcare costs associated with follow-up testing or unnecessary treatments. In contrast, baseline models may exhibit lower specificity, leading to a higher rate of false positives and potential diagnostic errors. The proposed model’s superior performance and reliability hold significant potential for clinical translation and integration into diagnostic workflows. By providing accurate and reliable MS detection capabilities, the model can assist clinicians in making timely and informed decisions, facilitating early intervention, and improving patient outcomes. In contrast, baseline models may lack the necessary accuracy and robustness to be effectively utilized in clinical settings.

The presence of data class imbalances, where the number of normal MRI scans may significantly outnumber abnormal scans, poses a challenge to model training and generalization. Addressing this imbalance is crucial to prevent biased model predictions and ensure robust performance across diverse patient populations and imaging protocols. DL models, including the proposed MLP with dropout regularization, often lack interpretability and explainability, making it challenging for clinicians to trust and understand the model’s decision-making process. Enhancing model interpretability through attention mechanisms, saliency maps, or model-agnostic methods can facilitate clinical adoption and improve trust in the model’s predictions.

While the proposed model demonstrates strong performance on the Kaggle MS dataset, its generalizability to real-world clinical settings and diverse patient populations remains to be validated. Variability in MRI acquisition protocols, image quality, and disease manifestations across different clinical sites and populations can impact the model’s performance and require additional data collection and validation efforts.

The proposed multi-modality MS detection model achieved exceptionally high accuracy, and several factors contribute to this impressive performance. One of the primary reasons is the rich spatial features extracted from MRI scans using DenseNet 201. MRI scans provide high-resolution images that reveal detailed structural anomalies associated with MS. DenseNet 201 excels in identifying these anomalies, particularly lesions, which are a hallmark of MS. The network captures intricate details about the size, shape, and distribution of these lesions, enhancing the model’s ability to detect even subtle signs of the disease. Additionally, the model identifies regions of brain atrophy, another critical indicator of MS, by detecting patterns of tissue loss and shrinkage. Changes in white matter, including the formation of plaques, are also effectively recognized, further distinguishing MS from other neurological conditions.

Another crucial factor is the incorporation of temporal dynamics from health records using Bi-LSTM networks. Health records provide sequential data that reflect the progression of MS over time. The Bi-LSTM network analyzes this temporal data to identify significant patterns, such as the progression of symptoms from mild to severe or the occurrence of relapse episodes. These patterns are essential for diagnosing MS accurately. Furthermore, the model examines patient responses to treatments over time, which helps in understanding the effectiveness of various therapies and

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**Table 3:** Statistical analysis outcomes.

<table>
<thead>
<tr>
<th>Models</th>
<th>AUROC</th>
<th>AUPRC</th>
<th>SD</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed model</td>
<td>99.3</td>
<td>98.9</td>
<td>0.0004</td>
<td>96.3</td>
</tr>
<tr>
<td>DenseNet 201</td>
<td>98.9</td>
<td>98.5</td>
<td>0.0002</td>
<td>95.8</td>
</tr>
<tr>
<td>EfficientNet B7</td>
<td>99.1</td>
<td>98.4</td>
<td>0.0005</td>
<td>96.1</td>
</tr>
<tr>
<td>La Rosa et al. (2022)</td>
<td>98.5</td>
<td>98.1</td>
<td>0.0007</td>
<td>95.9</td>
</tr>
<tr>
<td>Acar et al. (2022)</td>
<td>98.6</td>
<td>98.3</td>
<td>0.0012</td>
<td>95.8</td>
</tr>
<tr>
<td>Coronado et al. (2021)</td>
<td>98.7</td>
<td>98.5</td>
<td>0.0006</td>
<td>96.1</td>
</tr>
<tr>
<td>Narayana et al. (2020)</td>
<td>99.2</td>
<td>98.8</td>
<td>0.0016</td>
<td>95.9</td>
</tr>
<tr>
<td>Gaj et al. (2021)</td>
<td>98.8</td>
<td>98.1</td>
<td>0.0009</td>
<td>95.3</td>
</tr>
</tbody>
</table>

Abbreviations: AUPRC, area under precision–recall curve; AUROC, area under regional operating characteristic; CI, confidence interval; SD, standard deviation.
differentiating between different stages of MS. By capturing long-term trends and changes in a patient’s health trajectory, the Bi-LSTM network provides a comprehensive view that is vital for accurate diagnosis.

The feature fusion technique employed in the model plays a significant role in achieving high accuracy. By concatenating spatial features from MRI scans with temporal features from health records, the model creates a robust and holistic representation of each patient’s condition. This comprehensive approach ensures that both structural abnormalities and temporal patterns are considered, providing a more complete picture of the disease. The fusion of these complementary data sources leverages their combined strengths, resulting in a synergistic effect that enhances the model’s diagnostic capabilities. The integration of detailed spatial information with rich temporal dynamics enables the model to make more informed and accurate predictions.

The models from La Rosa et al. (2022), Acar et al. (2022), Coronado et al. (2021), Narayana et al. (2020), and Gaj et al. (2021) show strong performance in their respective evaluations. However, the proposed model’s superior metrics suggest that integrating MRI data with longitudinal health records provides a more comprehensive and accurate diagnostic tool.

For instance, Coronado et al. (2021) achieved an accuracy of 97.2%, which is impressive but still lower than the 99.8% accuracy of the proposed model. This difference underscores the advantage of the proposed model’s approach in leveraging the complementary strengths of multi-modal data.

The significance of the proposed method lies in its innovative approach to leveraging multi-modality data fusion for the detection of MS. Traditional diagnostic methods often rely solely on individual sources of information, such as MRI scans or health records. However, integrating these diverse data types, including MRI scans for spatial imaging data and health records for longitudinal patient information, allows for a more comprehensive and nuanced understanding of MS pathology and progression. The model’s enhanced accuracy and reliability are particularly noteworthy. By integrating DenseNet 201 for MRI feature extraction and Bi-LSTM networks for health record analysis, the model achieves a high accuracy of 99.2% in MS detection. This significant achievement underscores the effectiveness of combining spatial information from MRI with temporal dynamics from health records, enhancing diagnostic accuracy beyond what is achievable with either data type alone. Moreover, the fusion of MRI and health record data enables a holistic view of MS. It identifies structural abnormalities in the brain and considers the temporal patterns of disease progression and patient health history. This comprehensive approach is crucial for understanding the disease, from onset to progression.

Despite these promising results, the study encountered several challenges. Integrating multi-modality data posed significant technical difficulties, particularly in aligning and synchronizing MRI scans with health records. Data heterogeneity, arising from differences in data formats and sources, further complicated the fusion process. Additionally, obtaining high-quality, comprehensive datasets including detailed MRI scans and extensive health records was challenging, limiting the model’s training and validation potential. Another challenge was ensuring the model’s generalizability across diverse patient populations and healthcare settings. The initial dataset may not fully represent the variability seen in broader clinical practice, necessitating further validation studies. In addition, the complexity of the model requires substantial computational resources, which could limit its practicality in some clinical environments.

The reliability of proposed multi-modality MS detection model’s results can support physicians to provide early diagnosis. Several specific future steps and experiments are planned to achieve this validation. First, conducting clinical trials with diverse patient cohorts is crucial. These trials will involve collaborating with multiple healthcare institutions to recruit a wide range of patients, including those of various ages, genders, ethnic backgrounds, and stages of MS. Comprehensive MRI scans and longitudinal health records will be collected for each patient to test the model’s performance in real-world scenarios. The outcome measures will focus on evaluating the model’s diagnostic accuracy, precision, recall, and F1-score in identifying MS compared to standard diagnostic methods used by neurologists.

In addition to clinical trials, longitudinal studies for disease progression monitoring will be conducted. These studies will track patients over extended periods, with regular MRI scans and health record updates to monitor changes and progression in MS. The model’s ability to detect subtle changes in the disease state and its effectiveness in predicting relapses and disease advancement will be analyzed. Comparative analysis will be performed to compare the model’s predictions with actual clinical outcomes and neurologists’ assessments. This will help in understanding the model’s capability in providing accurate and timely information about disease progression.

CONCLUSIONS

The suggested method of using an MLP with dropout regularization and early stopping strategy for categorizing extracted features in MS detection shows potential for building precise and reliable diagnostic models. Researchers may extract detailed and useful features from MRI images by using sophisticated feature extraction methods like DenseNet 201 or EfficientNet B7. These features can capture subtle patterns that are symptomatic of problems related to MS. The addition of dropout layers to the MLP design adds a regularization method that improves the model’s capacity to generalize to new data and reduces overfitting problems. This boosts the model’s resilience and reliability. Furthermore, the early stopping method is a preemptive precaution to avoid overfitting the model. It does this by continuously evaluating the model’s performance on a validation set throughout training, guaranteeing that the final model gets the best possible generalization performance. By conducting thorough testing and assessment on various datasets, the suggested technique has shown promising outcomes, attaining a high level of accuracy and dependability in differentiating between normal and abnormal MRI scans that indicate MS. By combining dropout regularization with an early halting approach, the
model’s performance is improved and its decision-making process becomes more transparent and reliable, which is beneficial in clinical contexts. Furthermore, the suggested approach’s adaptability and capacity to be easily expanded make it compatible with current diagnostic processes. This provides doctors with useful tools to aid in making prompt and precise diagnosis of MS. The use of MLP with dropout regularization and early stopping techniques is a notable progress in MS diagnosis. It provides a strong and dependable option for using MRI-based biomarkers in clinical practice. Further studies and validation are necessary to improve and optimize the suggested strategy, leading to better accuracy in diagnosing MS, improved patient outcomes, and higher quality of care in managing the condition.

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