**MS insight:** An Intelligent Diagnostic Assistant Harnessing AI for Early Detection and Comprehensive Management of Multiple Sclerosis.

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**Abstract**

Detection and classification of diseases frequently relies on manual assessment by specialists across various medical fields. Consequently, the diagnostic process and monitoring of disease progression tend to be meticulous yet time-consuming. However, certain diseases, such as multiple sclerosis (MS), present formidable hurdles due to the imperative of timely diagnosis. Delayed detection of MS can lead to grave repercussions for patients, underscoring the need for innovative solutions to aid in early detection. The objective of this paper is to propose a mobile phone-based system designed to facilitate the early and accurate diagnosis of MS. Leveraging advancements in technology, our system aims to empower healthcare professionals, including newly graduated doctors, with tools to detect MS efficiently and reliably. By providing accessible and user-friendly diagnostic capabilities on a mobile platform, our system seeks to enhance the sensitivity and speed of MS diagnosis, thereby improving patient outcomes and quality of care. Through the integration of cutting-edge algorithms and medical knowledge, our proposed system represents a promising step towards addressing the diagnostic challenges associated with MS

# **Motivation and significance/Introduction**

# **1.1 The Problem**

Multiple sclerosis (MS) is a potentially disabling disease of the brain and spinal cord (central nervous system).

In MS, the immune system attacks the protective sheath (myelin) that covers nerve fibers and causes communication problems between your brain and the rest of your body. Eventually, the disease can cause permanent damage or deterioration of the nerve fibers.

Signs and symptoms of MS vary widely between patients and depend on the location and severity of nerve fiber damage in the central nervous system. Some people with severe MS may lose the ability to walk independently or ambulate at all. Other individuals may experience long periods of remission without any new symptoms depending on the type of MS they have.

Multiple sclerosis is an acquired inflammatory and neurodegenerative immuno-mediated disorder of the central nervous system, characterized by inflammation, demyelination and primary or secondary axonal degeneration. It clinically manifests with signs of multiple neurological dysfunctions (e.g. visual and sensory disturbances, limb weakness, gait problems and bladder and bowel symptoms) followed by recovery or by an increasing disability because of irreversible functional disability over time. However, more specific symptoms can be detected, such as fatigue, which is experienced by nearly 80% patients as interfering with their quality of life and productivity, regardless of the degree of disability and course status [1].

Immunoprophylactic therapies have not yet proven to be highly efficacious in modifying the disease course and are often associated with side effects further worsening patients’ quality of life and productivity. The disease shows heterogeneity with respect to its pathogenesis, clinical manifestations, prognosis and, most interestingly, with respect to its pathology. The etiology of MS is unknown. It is a complex multifactorial disorder, in which environmental factors are hypothesized to interact with genetically susceptible individuals. Pediatric MS and late-onset MS (i.e. clinical onset over the fifth decade) are rare.

Multiple sclerosis (MS) is the most common idiopathic inflammatory disease of the central nervous system [2]

The distinction between MS and other benign or fulminant inflammatory demyelinating disorders is based on quantitative, rather than qualitative, differences in chronicity and severity.

Primary progressive MS may differ from relapsing-remitting MS in MRI lesion frequency, immunogenetic profile, responsiveness to immunosuppressive treatment, and histology.

In 60% of patients, MS begins as a relapsing-remitting disease and evolves secondarily into a progressive neurological illness. Life expectancy is not substantially altered in patients with MS, particularly in the early years of the illness.

The rate of suicide has been reported to be increased sevenfold in MS patients. Up to 40% of patients with attacks severe enough to render them no ambulatory may not recover. At 15 years from MS onset, 50% of patients are disabled to the point at which they at least require a cane to walk a half block. Early age at onset, female sex, relapsing-remitting course at onset, and perhaps optic neuritis or sensory symptoms at onset and relatively few attacks in the first two years are associated with a favorable course.

Despite significant refinement in multiple sclerosis (MS) diagnosis in recent decades, no specific disease biomarker exists, as a result of which, confirming the diagnosis is not always a straightforward process. MS has heterogeneous clinical and imaging manifestations, which not only differ between patients, but also vary in individual patients over time [3].

Misdiagnosis remains a problem with significant clinical and psychosocial implications for both patients as well as health care providers. Although the problem of MS misdiagnosis is known, true incidence and prevalence is not.

One study conducted in four academic MS centers revealed over 50% of patients carried a misdiagnosis for at least 3 years, 70% had received disease-modifying therapy (DMTs), and 31% experienced unnecessary morbidity as a direct result.

A wide range of conditions can be mistaken for MS, including migraine, cerebral small vessel disease, fibromyalgia, functional neurological disorders, and neuromyelitis Optica spectrum disorders, along with uncommon inflammatory, infectious, and metabolic conditions.

Initial reports of MS misdiagnosis began at the end of the 1980s. Interestingly, if MRI had been available, diagnostic error would have been prevented in most cases. However, when MRI became widely used, overestimations of radiological findings started to be reported.

The problem of delayed diagnosis in Multiple Sclerosis (MS) is multifaceted, presenting significant challenges in the healthcare landscape. One key aspect is the complex nature of MS itself, characterized by a wide range of symptoms and varying progression among individuals. This complexity poses a challenge for healthcare professionals, particularly those less experienced in neurology, making early and accurate diagnosis a formidable task so MS diagnosis often involves a prolonged process, including multiple tests and consultations, leading to delays in initiating appropriate treatment.

Early symptom onset further complicates the diagnostic process, as symptoms may be subtle and overlap with conditions like Clinically Isolated Syndrome (CIS). Distinguishing between MS and CIS is crucial for timely and targeted interventions, yet the current diagnostic reliance on MRI imaging, while valuable, may not always provide a conclusive diagnosis, especially in the disease's early stages.

The limited availability of resources and tools for early MS diagnosis exacerbates the problem. The scarcity of effective diagnostic technologies, particularly those leveraging artificial intelligence, contributes to missed opportunities for early intervention and disease management. Additionally, accessibility to specialized healthcare, essential for accurate MS diagnosis, is constrained in certain geographic areas, impacting patients' ability to obtain timely and accurate diagnoses.

Educational and training gaps further hinder the diagnostic process. Less experienced healthcare professionals may lack the necessary knowledge to recognize the nuanced symptoms of MS, highlighting the need for comprehensive solutions that bridge these gaps and facilitate accurate diagnoses even among providers without extensive neurology experience.

Statistics on MS: It is estimated that there are approximately 2.8 million people worldwide living with multiple sclerosis.

The number of multiple sclerosis patients in Egypt has reached 60,000, one of the largest countries in the Middle East with several patients.

MS is commonly attributed to high familial risks, decreasing with relatedness, which indicates a large genetic component involved in the disease etiology. The relative risks estimated were lower than usually reported, with a sibling relative risk of 7.1 and no significant differences between the sexes. The heritability was estimated to be 64% and the environmental 36% with a non-significant shared environmental component of 1% [4].

MS is a disease more common in women than men, and an increase in the women-to-men ratio has been reported in several countries. However, a report from Sweden did not show this increase in women. An increase among women compared to men was identified, and when comparing against the previous study, an inclusion bias, presumably caused by a higher mortality rate among the oldest men, was identified.

## **The available tools and gaps found**

In the literature survey focused on Multiple Sclerosis (MS) solutions, the existing landscape primarily consists of applications that aim to support individuals living with MS. These applications commonly offer services such as tracking and managing MS symptoms and treatments, creating connections, and providing support within the MS community, and offering simple guidelines to improve the quality of life for those affected by the condition .

While these applications play a valuable role in supporting individuals already diagnosed with MS, the notable gap lies in the lack of solutions specifically designed for early diagnosis prediction using artificial intelligence (AI). The current solutions tend to focus on managing and alleviating symptoms rather than predicting or diagnosing the condition at its early stages.

The literature review highlights a need for innovative tools that can provide more proactive and predictive healthcare solutions, especially in the context of MS. By incorporating AI into the diagnostic process, there is an opportunity to revolutionize the way MS is identified, particularly during the early onset of symptoms. This shift could significantly impact the timeliness and accuracy of diagnoses, potentially leading to more effective interventions and improved outcomes for individuals with MS.

The absence of AI-driven diagnostic prediction tools in the current solutions emphasizes the potential for the proposed system, which aims to fill the identified gap by utilizing AI to assist in the early and accurate diagnosis of MS, thereby addressing a critical need in the healthcare sector.

## **Solution**

1- MS insight is a comprehensive, patient-focused app that offers an innovative approach to MS diagnosis and management.

2- It leverages advanced artificial intelligence and machine learning algorithms to provide accurate and efficient diagnosis results, providing them with treatment recommendations.

3- The diagnostic test results obtained through our app assist healthcare professionals in confirming their diagnosis

4- Our app provides a diagnosis within minutes, enabling early intervention and improved patient outcomes. It's a game-changer in the world of healthcare.

# **Related Work**

Initially ,MS diagnosis is complex because its signs and symptoms are widespread, having a similarity with the symptoms of other neurological diseases [5] . In the present study evaluate utility of machine learning

techniques to diagnosis MS and provide long-term predictions of the degree of disability in MS patients based on clinical data and RNFL thickness

measurements acquired by OCT [6]. Studies have shown that RNFL thickness, measured by OCT, is a useful parameter to distinguish MS patients from

healthy controls, Rothman et al. [7] evaluated the capability of OCT data to predict the disability status 10 years later in 172 MS patients, applying linear regression models . Garcia-Martin et al. [8] used an artificial neural network

(ANN) in combination with OCT data to diagnose MS. Zhao et al. [9] evaluated the utility of SVM and logistic regression to predict the progression of MS- associated disability using brain MRI data acquired over 5 years. Yperman et al. [10] analysed random forest and logistic regression to predict disability

progression after 2 years using EP time series. Arani et al. [11] used rule-

based, fuzzy logic (FL), and artificial neural network (ANN) to diagnosis MS. Seccia et al. [12] reviewed studies that used computer-aided diagnosis (CAD) using clinical data alone or in conjunction with other forms of data to build

prognostic models for MS . Ion-Margineanu et al. [13] utilized three classifiers, LDA, RF, and SVM with radial base function (SVM-RBF), to classify patients into one of the four MS subtypes. Ettema et al. [14] examined the effectiveness of an electronic nose (eNose) in detecting MS based on exhaled breath

analysis.Sharifmousavi and Borhani [15] provide a simple and efficient method for detection of MS using vitamin D3, vitamin B12, and selenium

levels. Similarly, Wang et al. [16] aimed to find a method of detecting the early phases of MS. They used 676 MRI slices holding plaques of 38 patients and 880 MRI scans of 34 healthy people. Wang et al[16] introduced a six-layer stochastic pooling CNN to detect MS with multiple-way data augmentation.

# **3.Software description**

MS insight is a comprehensive, patient-focused app that offers an innovative approach to MS diagnosis and management. It leverages advanced artificial intelligence and machine learning algorithms to provide accurate and efficient diagnosis results , provide them with treatment recommendations. The diagnostic test results obtained through our app assist healthcare professionals in confirming their diagnosis. Our app provides a diagnosis within minutes, enabling early intervention and improved patient outcomes. It's a game-changer in the world of healthcare.

## **3.1Software Architecture**

In the modern era of healthcare, technology plays a crucial role in improving diagnosis and treatment. One such area is the detection of diseases like Multiple Sclerosis (MS), which can benefit significantly from advanced software solutions. we'll explore the software architecture for a project aimed at MS insight, focusing on the frontend, backend, and integration of ai models.

**Frontend Development with React Native**

React Native is a popular choice for building mobile applications due to its cross-platform capabilities and efficiency in creating native-like experiences. For the MS insight app, the frontend will be developed using React Native to ensure compatibility with both iOS and Android devices.

**Features of the Frontend:**

* + **User Interface (UI):** The UI will include screens for user authentication, capturing relevant medical information (such as symptoms and medical history) and displaying test results.
  + **Data Input:** Users will be able to input data through forms and interfaces designed to collect information required for MS detection, such as neurological symptoms, demographic details and brain MRI.
  + **Integration with Backend:** The frontend will communicate with the backend to send user input, receive processed data, and display relevant information to the user.

**Backend Development for API:**

The backend of the MS insight app will be responsible for processing user input, interfacing with Deep learning models, and providing the necessary data to the frontend. It will be built using a framework Flask (Python) to create a RESTful API

**Key Components of the Backend:**

* + **API Endpoints:** The backend will define several endpoints to handle different types of requests, such as user authentication, data submission, and result retrieval.
  + **Data Processing:** Upon receiving user data, the backend will preprocess it, validate it, and pass it to the Deep learning models for analysis.
  + **Deep learning Models Integration:** The backend will integrate with Deep learning models trained to detect MS based on the input data. These models will classify the data and provide a prediction or diagnosis.
  + **Database Management:** The backend may use a database to store user data, authentication tokens, and other relevant information. This database will ensure data persistence and facilitate efficient data retrieval.

**Integration of Deep learning Models**

Artificial intelligence plays a central role in the MS insight app, as it enables the prediction and diagnosis of MS based on user input. The machine learning models will be trained using a dataset containing relevant features and corresponding MS labels. These models will then be integrated into the backend to enable real-time predictions.

**Deep learning Workflow:**

* **Data Collection**: Relevant data for training the Deep learning models will be collected from various sources, such as medical records and research datasets.
* **Feature Extraction:** Features relevant to MS insight, such as demographic information, symptoms, and medical history, will be extracted from the collected data.
* **Model Training:** Deep learning models, such as Convolutional Neural Network (CNN) Long short-term memory (LSTM), will be trained using the extracted features and corresponding MS labels.
* **Model Integration:** The trained models will be integrated into the backend API, allowing them to receive input data, make predictions, and return the results to the frontend.

**tools and technologies**

This is an overview of the tools and technologies used in our software architecture to manage MS data and implement AI-driven pest segmentation solutions.

**Datasets:**

Our project relies on the

* **Multiple Sclerosis Disease dataset** :- These data were collected through prospective cohort studies on newly diagnosed Mexican mestizo CIS patients who were presented at the National Institute of Neurology and Neurosurgery (NINN) in Mexico City, Mexico, between 2006 and 2010 [17]
* **Floodlight Open dataset :-** These data were collected throughout the study contains assessments of participants' ability (with and without self-declared MS) to perform simple tasks on their smartphones with the aim of understanding the effects of MS on mood, cognition, hand-motor function, postural stability, and gait.[18 ]
* **Multiple Sclerosis dataset :- t**he study dataset comprised axial and sagittal FLAIR MRI images of the brain that were prospectively acquired from 72 MS and 59 non-diseased “healthy” male and female patients who attended the Ozal University Medical Faculty in 2021.[ 19 ]

**AI Models:**

We employ various AI models including GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory), and CNN (Convolutional Neural Network) for the analysis and segmentation of lesions associated with Multiple Sclerosis.

**Development Environment:**

Our development environment encompasses Visual Studio Code, Jupiter Notebook, and Kaggle Notebook, providing versatile platforms for coding, experimentation, and collaborative development.

**Frontend:**

For the frontend, we utilize JavaScript (React) to develop both the website and the mobile application using React Native. This ensures a consistent user experience across different platforms.

**Backend:**

Python, along with the Flask framework, powers our backend infrastructure, facilitating data processing, model inference, and API endpoint management to support seamless communication between the frontend and AI models.

This paper serves as a reference guide, offering insights into the technologies employed in our software architecture, with a focus on managing Multiple Sclerosis Disease data and implementing AI-driven lesion segmentation solutions

## **3.2Software functionalities*:***

The system will be seamlessly integrated into real-life scenarios to enhance the early detection of Multiple Sclerosis (MS). Users, primarily individuals experiencing symptoms or seeking preventive healthcare, will engage with the system through a dedicated mobile application. The application will feature four distinct modules for comprehensive diagnosis (see fig1):

**Symptoms-based Diagnosis:**

* Users will input their symptoms into the application, providing crucial data for an initial evaluation of their health status.
* Additionally, users will share their health history and personal information, enabling the system to conduct a thorough assessment of the likelihood of an MS infection (see fig1):.

**Floodlight Tests-based Diagnosis:**

smartphone for tasks like answering daily questions, completing an Information Processing Speed Baseline Test, drawing shapes, assessing

mobility, and participating in a Two Minute Walk Test and Static Balance assessment.

* These Floodlight tests will comprehensively investigate the impact of MS on mood, cognition, hand motor function, postural stability, and gait.
* Test results will be instrumental in the final diagnosis, providing a holistic view of the user's cognitive and physical health.

**MRI Scan Integration:**

* Users will have the option to upload MRI scans through the application.
* The system will utilize advanced segmentation analysis based on the provided MRI data, identifying affected areas, and contributing to the predictive modeling for MS detection (see fig1):

**Treatment recommendations:**

* A diagram of a medical system

  Description automatically generated with medium confidenceThe application offers patients access to cutting-edge treatment modalities, ensuring they stay informed about the most recent and advanced approaches to healthcare.

Fig 1 MS insight system architecture

# **3.3 Results and discussion**

CNN

First Detail of the CNN model used in the case of MS diagnosis:

Generally, for each disease a new CNN model is trained on the

available public datasets. In the case of MS disease for example,

the CNN architecture consists of the five following layers:

The first layer is a Convolutional layer (Conv2D) with 32 filters of size (3, 3) and ReLU activation. This layer is responsible for learning features from the input images.

Following the Convolutional layer, there's a MaxPooling layer (MaxPooling2D) with a pool size of (2, 2), which helps in reducing the spatial dimensions of the representation.

This pattern of Convolutional and MaxPooling layers is repeated twice more, with 64 and 128 filters respectively, gradually increasing the depth of learned features while reducing spatial dimensions.

After the convolutional layers, there's a Flatten layer to flatten the 3D output to 1D, preparing it for input to the fully connected layers.

Two fully connected (Dense) layers follow. The first one has 128 units with ReLU activation and a dropout rate of 50%, which helps prevent overfitting. The last layer is the output layer with a SoftMax activation, which is suitable for multi-class classification tasks like yours.

The model is compiled using the Adam optimizer, which is an efficient optimizer for training neural networks.

Categorical cross-entropy is used as the loss function, which is suitable for multi-class classification problems. Afterwards, it is trained on the training data for 30 epochs with a batch size of 32.

Our CNN model have achieved high accuracy without overfitting, as evidenced by the small loss function depicted in the (fig 2).

LSTM

Second Detail of the LSTM model used in the case of MS diagnosis:

This LSTM model is more complex than the CNN model and is suitable for sequential data such as time series or text data. So, we used it to diagnose multiple sclerosis based on the set of data that he would take from the user.

the LSTM architecture consists of the five following layers:

The model starts with an LSTM layer (LSTM) with 64 units. The input shape parameter indicates the input shape, where sequence length represents the length of each sequence and X\_sequences. shape [2] represents the number of features in each time step of the sequence.

The return sequences=True argument in the first two LSTM layers indicates that they return sequences rather than single vectors. This is important because subsequent LSTM layers expect sequences as input.

The second LSTM layer is identical to the first one.

The third LSTM layer doesn't have return sequences=True, which means it returns only the last output in the output sequence.

Finally, there's a Dense layer with SoftMax activation.

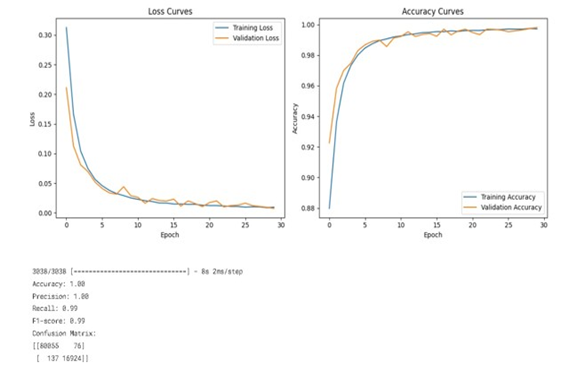
The model is compiled using the Adam optimizer, which is an efficient optimizer for training neural networks.

Categorical cross-entropy is used as the loss function, which is suitable for multi-class classification problems. Afterwards, it is trained on the training data for 10 epochs with a batch size of 64

Our LSTM model has achieved high accuracy without overfitting, as evidenced by the small loss function depicted in the (fig 3).

# **3.4 Sample code snippets**

Finally, here are some graphs that show the accuracy of the algorithms that have been used.



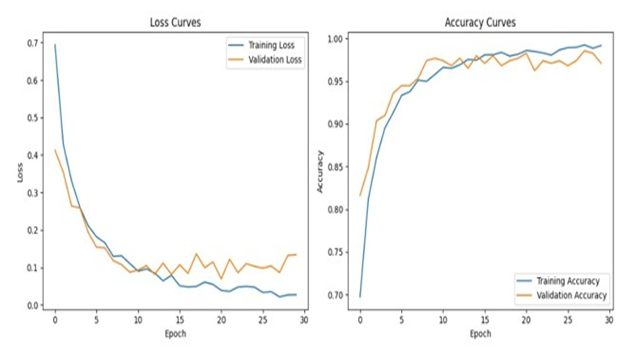
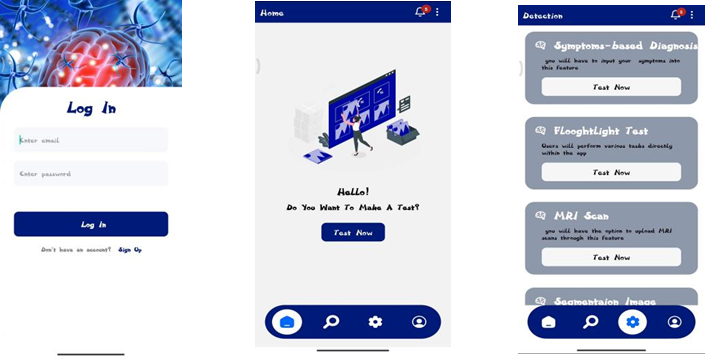
Fig 2 CNN graph

Fig 3 LSTM graph

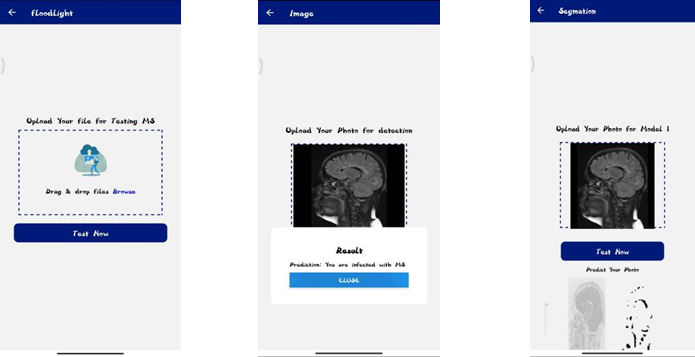
# **4 Illustrative examples**

The system will be seamlessly integrated into real-life scenarios to enhance the early detection of Multiple Sclerosis (MS). Users, primarily individuals

experiencing symptoms or seeking preventive healthcare, will engage with the system through a dedicated mobile application. The application will feature three distinct modules for comprehensive diagnosis



(A) (B) (C)



(D) (E) ( F )

Example of using the MS *insight* application to detect and diagnose multiple sclerosis disease

The user experience while utilizing the application is described below in order to make clear how the use cases were implemented:-

# **Create an account or log in to an existing one :**

The user can create a new account by clicking on the ‘‘Sign upʼʼ button. or can log in to am existing one by entering the email and the password of the user then clicking on ‘‘Log inʼʼ button.

# **Take your test:**

here the user can press the ‘‘Test now ʼʼ button to start their diagnoses

# **Test choices :**

there is 4 different tests that the user can make to detect the disease the first one is ‘’symptoms-based **Diagnosis’’** in which Users will input their symptoms into

the application, providing crucial data for an initial evaluation of their health status.

Additionally, users will share their health history and personal information, enabling the system to conduct a thorough assessment of the likelihood of an MS infection.

# **Floodlight Tests-based Diagnosis:**

Another type of tests, These Floodlight tests will comprehensively investigate the impact of MS

on mood, cognition, hand motor function, postural stability, and gait.

Test results will be instrumental in the final diagnosis, providing a holistic view of the user's cognitive and physical health.

# **MRI-Test:**

Users have the option to upload MRI scans through the application to diagnose their condition based on these MRIs

# **segmentation analysis:**

The system will utilize advanced segmentation analysis based on the

provided MRI data, identifying affected areas ‘ʼthe dark spacesʼʼ, and contributing to the

predictive modeling for MS detection.

The system's flexibility accommodates different user scenarios, enhancing the overall experience

and encouraging proactive engagement for early detection and management of Multiple Sclerosis.

# **5. Impact**

## **5.1 Use case scenarios and target audience**

The application offers a new way to MS diagnoses and management leveraging the use of deep learning technologies. Neurologists, medical researchers, and healthcare professionals will benefit from its capability to provide fast and accurate classification of MS cases. As the most dangerous thing about MS disease is it can lead to varying degrees of disabilities over time, the need for fast and accurate results is at its most. The application will reduce the time and effort required for accurate disease identification which in the end will prevent the disease progress by providing the early treatment and enable doctors to take the right actions about each individual case. Another rising problem with MS disease is the lack of healthcare professionals with specialized knowledge and experience in diagnosing and treating multiple sclerosis as well as the geographical or logistical barriers that limit their access to specialized healthcare professionals. Hence, having a mobile application that utilizes AI algorithms and provide accurate and fast results which anyone could simply download will cover this gap.

## **5.2 Innovative aspects**

Our application brings modern software technologies to the field of neurological disease classification by integrating machine learning and deep learning algorithms. These advanced techniques adhere to the smallest details while classifying any data, allow for nuanced pattern recognition, enhance the accuracy of diagnosis, and reduce the amount of time needed to diagnose each case and overcome the scarcity of healthcare professionals. The application aims to provide more objective and accurate information to facilitate decision-making by doctors, neurologists, medical researchers, and healthcare and, above all, reduce waiting times before receiving a final diagnosis.

## **5.3 Software accessibility**

The software is designed with accessibility in mind, ensuring an intuitive user interface for healthcare professionals with different technical backgrounds to ensure they have the best user experience.

## **5. 4 Future research directions:**

Our project opens avenues for future research by raising pertinent questions. Areas such as refining the model with additional patient data, exploring predictive analytics for disease progression, and investigating the impact of environmental factors on MS development present exciting prospects for further research and investigation.

## **5. 5 The added value to existing research**

The application contributes significantly to existing research by providing a more efficient and accurate tool for MS classification. Its advanced capabilities enhance the understanding of disease patterns and aid in refining research questions related to the diagnosis and treatment of Multiple Sclerosis.

## **5. 6 Changes that will happen in daily practice**

Healthcare professionals and Doctors using our software will witness a transformative shift in their daily practice. The tool accelerates diagnosis, allowing for immediate intervention and personalized treatment plans. This not only improves patient outcomes but also enhances the overall efficiency of healthcare delivery.

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