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# BRAIN DISEASE CLASSIFICATION ANDAGE ESTIMATION USING MRI

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***ABSTRACT***

***Deep neural networks can accurately predict the chronological age of healthy individuals from brain images, and the predicted brain age may serve as a biomarker for aging process disorders. Therefore, in this proposed procedure, we are applying the cascade network of deep learning, which is a ResNet, and also one of the machine learning algorithms titled MobileNet. The brain MRI pictures that are divided into three classes—Normal, which is unaffected by any disease, and various classes affected by Alzheimer's disease (AD) and mild cognitive impairment—are trained using these algorithms (MCI). From this point, we can also determine the ages of the classified photographs.***

***The MRI image dataset will be trained using ResNet and MobileNet, and it will be used to do classification.***

***Keywords: ResNet, AD, MCI, and neural network.***

## INTRODUCTION

The goal of the study field known as "brain disease classification from MRI" is to create algorithms and models that can automatically identify and categorize various brain diseases based on magnetic resonance imaging (MRI) data. This can be helpful for the early detection and diagnosis of illnesses including Alzheimer's, Parkinson's, multiple sclerosis, and other brain diseases in a clinical context. The prompt delivery of appropriate care and therapy to patients depends on the accurate and reliable identification of various brain illnesses.

Image processing, machine learning, and deep learning techniques are frequently employed for this job to analyze the MRI scans and extract pertinent information for disease classification. Reducing the duration of therapy and increasing patient outcomes through the precise classification of brain illnesses using MRI can enhance patient diagnosis and prognosis

## LITERATURE SURVEY

A thorough analysis of the body of work in this field is often required for a literature review on brain disease classification from MRI. This involves analyzing research that has examined the use of various image processing, machine learning, and deep learning techniques for this purpose, as well as research that has examined the use of MRI to categorize various brain illnesses.

Some of the major discoveries that might be made through the literature review are as follows:

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- The classification of brain diseases using various MRI modalities, including T1-weighted, T2-weighted, and diffusion-weighted MRI.
- Using various image processing methods to extract important information from the MRI scans, such as segmentation and registration.
- The classification of brain diseases using a variety of machine learning and deep learning techniques, including support vector machines, random forests, and convolutional neural networks (CNN).
- evaluating the performance of the models using various assessment criteria, including accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC).
- The drawbacks of the current approaches and the difficulties that need to be solved in upcoming studies.

The literature review may also highlight the most innovative approaches and results, the datasets used, and the effectiveness of the models. This can help suggest topics for further research and provide significant insights about the state-of-the-art in brain disease classification using MRI.

**EXISTING APPROACHES**

**[1] ] C. R. Jack Jr.:** The strongest case for the theory that abnormal processing of the peptide -amyloid (A) causes the onset of Alzheimer's disease (AD) and the subsequent formation of A plaques in the brain is supported by the data at hand.

While a person's cognitive abilities are still normal, this procedure takes place.

Reductions in CSF A-42 and higher amyloid PET tracer retention are biomarkers of brain amyloidosis.

Neuronal dysfunction and neurodegeneration emerge as the main pathological processes after a lag period that differs from patient to patient.

Increased CSF tau and structural MRI measurements of brain atrophy are biomarkers of neuronal injury and neurodegeneration.

Synaptic dysfunction, which is evidenced by decreased fluorodeoxyglucose uptake on PET, occurs concurrently with neurodegeneration.

Here, a paradigm is put forth that connects disease stage to AD biomarkers, with A biomarkers as the disease stage.

**[2] G. Spulber:** Knowing which mild cognitive impairment (MCI) subjects go on to develop Alzheimer's disease is crucial for both clinical and scientific purposes (AD).
The accelerated whole-brain atrophy seen in AD patients may have helped with the forecast.

data as the essential component for accurate prediction.

Sequential MRI scans of 102 MCI patients from the Kuopio University Hospital were used to describe whole brain atrophy rates using iterative principal component analysis (IPCA).
When we modelled the probability of progression to probable AD, we discovered that each additional percent of annualised whole brain atrophy rate was linked to a higher odds ratio (OR) of progression (OR = 1.300, p = 0.01, 95% CI=1.05 -1.60).
Our research shows a connection between the rate of whole-brain atrophy and the subsequent rate of

**[3] J. Dukart, M. L. Schroeter, and K. Mueller:**

Using support vector machine classification (SVM) or voxel-based morphometry, we suggest a straightforward method to account for the potential effects of confounding variables like age before statistically analysing magnetic resonance imaging (MRI) data (VBM). Based on MRI data with and without prior age correction, we analyse the SVM classification findings for 79 healthy control subjects and 80 AD patients. Furthermore, we compare VBM findings for the comparison of three distinct groups of AD patients with varying ages with the same group of control subjects obtained either without including age as a covariate or with prior age correction using the suggested method. The findings indicate that the strategy put forth in this work is usually suitable for removing confounding factors like age from

**[4] K. Franke, G. Ziegler, S. Kloppel, and C. Gaser:**

Early detection of abnormal brain anatomy, such as that seen in Alzheimer's disease (AD), that deviates from the typical pattern of development and atrophy, has the potential to enhance clinical outcomes through early intervention. Here, using a kernel method for regression, we present a framework for quickly and accurately determining the age of healthy subjects from their T-1-weighted MRI scans. Over 650 healthy volunteers between the ages of 19 and 86 who were drawn from four different scanners were used to test

this technique. The framework produced a correlation of r = 0.92 between the estimated and the actual age in the test samples and a mean absolute error of 5 years, demonstrating that it is a reliable, scanner-independent, and effective method for age estimation in healthy subjects. The outcomes showed that the success of

**[5] J. H. Cole:**

Neuroimaging data analysis using machine learning can successfully forecast chronological age in healthy individuals. Cognitive impairment and illness have been linked to deviations from healthy brain ageing. To strengthen the case for "brain-predicted age" as a biomarker of unique differences in the brain ageing process, we applied a predictive modelling method based on deep learning, particularly convolutional neural networks (CNN), to both preprocessed and raw T1-weighted MR data. ta On a sizable dataset of healthy adults (N = 2001), we first wished to demonstrate the reliability of CNN's brain-predicted age. Next, we used a group of 62 female monozygotic and dizygotic twins to determine the heritability of brain-predicted age. Finally, we looked at the reliability of brain-predicted outcomes across multiple centres and test-retest

## METHODOLOGY

The process for classifying brain diseases and estimating age using MRI typically entails three crucial steps:

1. Image pre-processing: The MRI scans are cleaned and prepared for analysis at this stage. For example, the image might be cleaned up, cropped, and registered to a predefined template.
2. Feature extraction: At this stage, relevant features from the MRI scans are extracted that can be used to estimate age and classify diseases. This can entail taking the scans' morphological, textural, and intensity-based properties.
3. Model training and evaluation: This phase entails

classification. To train and test a reliable model, this dataset must be both huge and diverse.

3 Pre-processing of the images: The MRI scans must be cleaned up of any artifacts or noise and registered to a standard template. The model must be resistant to differences in picture acquisition across many scanners and patients; therefore, this is crucial.

deep learning model using the retrieved features. The model's performance in disease categorization and age prediction is then evaluated using a collection of labeled MRI data.

4. Model deployment: The model can be used in a clinical context to automatically detect and diagnose brain illnesses as well as to estimate age after it has been trained and evaluated.

It's important to keep in mind that these procedures may change based on the precise methodology and dataset utilized. To further enhance the performance of the models, several techniques, including CNN, RNN, and other deep learning architectures, are also applied.

## IMPLEMENTATION

The proposed software system's general layout is depicted in the architecture diagram. It offers a comprehensive summary of the relationships between the different components. It condenses the software system's overall view into a manageable manner.

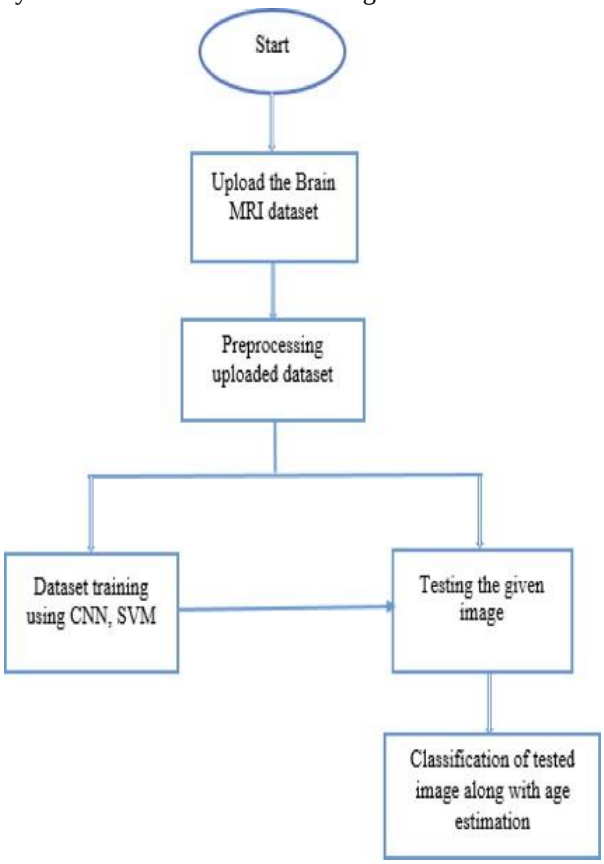


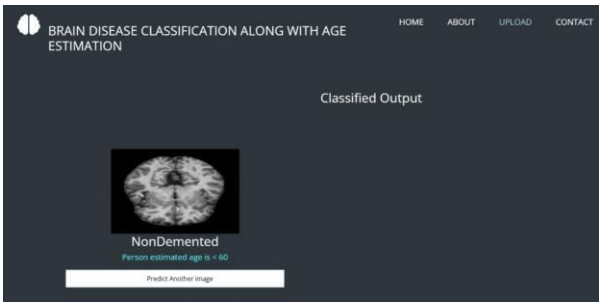

fig1: state chart of implementation

1. Data collection is the first step in the process, which entails gathering a dataset of MRI scans along with the labels that correlate to each image for age and disease

3. Feature extraction: To extract the features, the pre-processed MRI scans must be used. The model uses these qualities as inputs to classify diseases.
4. Model training and evaluation: Using the extracted features as input, a machine learning or deep learning model is trained and assessed using a collection of labeled MRI scans. Metrics including accuracy, precision, recall, and AUC are used to assess the model's performance.
5. Model deployment: The model can be used in a clinical context to automatically detect and diagnose brain illnesses as well as to estimate age after it has been trained and evaluated. This can be accomplished by incorporating the model into a software program that radiologists and other healthcare professionals can use. It's important to keep in mind that, based on the specific method and dataset used, the implementation of these steps may change. Additionally, a well-known deep learning framework like Tensorflow can be used for the implementation.

**DATA SET**

A total of 962 resumes and 25 job categories comprise the utilized dataset. All resumes in the dataset are full-size, detailed resumes. The dataset is a balanced dataset. Categories of job roles include:




**EXPERIMENTAL RESULTS**

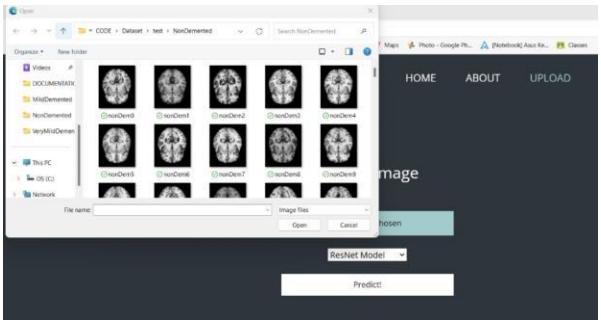
After installing the Python environment and the required modules, the application is ready for execution and results. Firstly, when we execute the application file, a window opens with three buttons.

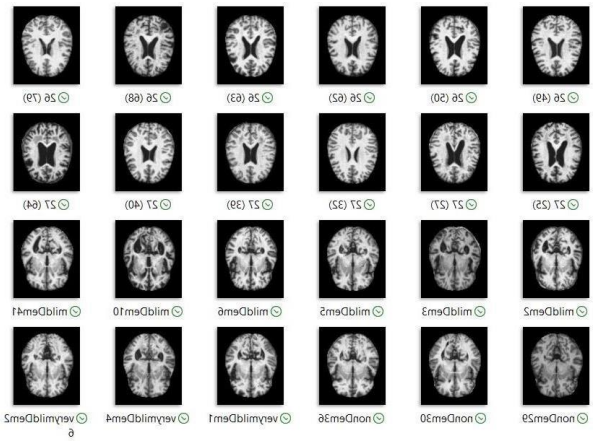
**CONCLUSION AND FUTURE SCOPE**

In this experiment, we have successfully identified whether the brain MRI scanned images are normal, affected by mild cognitive impairment, or caused by Alzheimer's disease. Based on the output that has been classified, the age is also estimated in addition to the categorization. The CNN and SVM algorithms, which are both based on machine learning, are used in this procedure. If the person's information is missing, this proposed process can be expanded further and used to estimate their age. It can also be used to suggest a diagnosis based on the person's estimated age and the disease that affected them.

They are predicted, reset, and closed if the user clicks on the predict button without entering any text. The system responds with information saying, “Content is empty." Please enter the appropriate input." The corresponding picture is shown in the diagram.

If the user clicks on the "predict" button after giving the input text, the system goes through a process to give results. The system is expected to give the output that makes people like recruiters and applicants choose their employees and careers. The below image shows an output, where we can see that after entering the candidate's resume, the output is displayed as "database developer" along with the confidence percentage. The top 5 job categories for the resume are shown.





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