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BRAIN DISEASE CLASSIFICATION WITH AGE ESTIMATION FROM MRI

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ABSTRACT

The Chronological age of healthy people is able to be predicted accurately using deep neural networks from neuroimaging data, and the predicted brain age could serve as a biomarker for detecting aging-related diseases. Hence, in this proposed method we are using the cascade network of the deep learning which is a Convolutional Neural Network (CNN) and also the one of the machine learning algorithms named Support Vector Machine (SVM). These algorithms are been used to train the brain MRI images which considered in the three classes as the Normal which is not effected with any disease and the other classes which were effected with Alzheimer's disease (AD) and Mild Cognitive Impairment (MCI). From which we can also find out the ages from the classified images. CNN and SVM are mainly used for the training of the MRI image dataset, upon where the classification will be performed along with the age estimation.

Keywords: Alzheimer's disease (AD) and Mild Cognitive Impairment, CNN, deep learning, SVM, machine learning

1. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease that usually starts slowly and progressively worsens. It is the cause of 60–70% of cases of dementia. The most common early symptom is difficulty in remembering recent events. As the disease advances, symptoms can include problems with language, disorientation (including easily getting lost), mood swings, loss of motivation, self-neglect, and behavioral issues. As a person's condition declines, they often withdraw from family and society. Gradually, bodily functions are lost, ultimately leading to death. Although the speed of progression can vary, the typical life expectancy following diagnosis is three to nine years. The cause of Alzheimer's disease is poorly understood.

There are many environmental and genetic risk factors associated with its development. The strongest genetic risk factor is from an allele of APOE. Other risk factors include a history of head injury, clinical depression, and high blood pressure. The disease process is largely associated with amyloid plaques, neurofibrillary tangles, and loss of neuronal connections in the brain. A probable diagnosis is based on the history of the illness and cognitive testing with medical imaging and blood tests to rule out other possible causes. Initial symptoms are often mistaken for normal aging. Examination of brain tissue is needed for a definite diagnosis, but this can only take place after death. Good nutrition, physical activity, and engaging socially are known to be of benefit generally in aging, and these may help in reducing the risk of cognitive decline and Alzheimer's; in 2019 clinical trials were underway to look at these possibilities. There are no medications or supplements that have been shown to decrease risk.

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No treatments stop or reverse its progression, though some may temporarily improve symptoms. Affected people increasingly rely on others for assistance, often placing a burden on the caregiver. The pressures can include social, psychological, physical, and economic elements. Exercise programs may be beneficial with respect to activities of daily living and can potentially improve outcomes. Behavioral problems or psychosis due to dementia are often treated with antipsychotics, but this is not usually recommended, as there is little benefit and an increased risk of early death.

As of 2015, there were approximately 29.8 million people worldwide with AD with about 50 million of all forms of dementia as of 2020. It most often begins in people over 65 years of age, although up to 10 per cent of cases are early-onset affecting those in their 30's to mid-60. Women get sick more often than men. It affects about 6% of people 65 years and older. In 2015, all forms of dementia resulted in about 1.9 million deaths. The disease is named after German psychiatrist and pathologist Alois Alzheimer, who first described it in 1906. Alzheimer's financial burden on society is large, on par with the costs of cancer and heart disease, with a 2013 study estimating an annual cost of $200 billion (equivalent to $222 billion in 2020) in the US alone.

In people with Alzheimer's disease, the increasing impairment of learning and memory eventually leads to a definitive diagnosis. In a small percentage, difficulties with language, executive functions, perception (agnosia), or execution of movements (apraxia) are more prominent than memory problems. Older memories of the person's life (episodic memory), facts learned (semantic memory), and implicit memory (the memory of the body on how to do things, such as using a fork to eat or how to drink from a glass) are affected to a lesser degree than new facts or memories.

Progressive deterioration eventually hinders independence, with subjects being unable to perform most common activities of daily living. Speech difficulties become evident due to an inability to recall vocabulary, which leads to frequent incorrect word substitutions (par aphasias). Reading and writing skills are also progressively lost. Complex motor sequences become less coordinated as time passes and Alzheimer's disease progresses, so the risk of falling increases. During this phase, memory problems worsen, and the person may fail to recognize close relatives. Long-term memory, which was previously intact, becomes impaired. Progressive deterioration eventually hinders independence, with subjects being unable to perform most common activities of daily living. Speech difficulties become evident due to an inability to recall vocabulary, which leads to frequent incorrect word substitutions (par aphasias).

2. LITERATURE SURVEY

C. R. Jack Jr: Currently available evidence strongly supports the position that the initiating event in Alzheimer's disease (AD) is related to abnormal processing of β-amyloid (Aβ) peptide, ultimately leading to formation of Aβ plaques in the brain. This process occurs while individuals are still cognitively normal. Biomarkers of brain β-amyloidosis are reductions in CSF Aβ42 and increased amyloid PET tracer retention. After a lag period, which varies from patient to patient, neuronal dysfunction and neurodegeneration become the dominant pathological processes. Biomarkers of neuronal injury and neurodegeneration are increased CSF tau and structural MRI measures of cerebral atrophy. Neurodegeneration is accompanied by synaptic dysfunction, which is indicated by decreased fluorodeoxy glucose uptake on PET. Here a model is proposed that relates disease stage to AD

biomarkers in which Aβ biomarkers become abnormal first, before neurodegenerative biomarkers and cognitive symptoms, and neurodegenerative biomarkers become abnormal later, and correlate with clinical symptom severity.

Spulber: For both clinical and research reasons, it is essential to identify which mild cognitive impairment (MCI) subjects subsequently progress to Alzheimer's disease (AD). The prediction may be facilitated by accelerated whole brain atrophy exhibited by AD subjects. Iterative principal component analysis (IPCA) was used to characterize whole brain atrophy rates using sequential MRI scans for 102 MCI subjects from the Kuopio University Hospital. We modelled the likelihood of progression to probable AD, and found that each additional percent of annualized whole brain atrophy rate was associated with a higher odds ratio (OR) of progression (OR=1.30, p=0.01, 95% CI=1.05-1.60). Our study demonstrates an association between whole brain atrophy rate and subsequent rate of clinical progression from MCI to AD. These findings suggest that IPCA could be an effective brain-imaging marker of progression to AD and useful tool for the evaluation of disease-modifying treatments.

J. Dukart, M. L. Schroeter, and K. Mueller: Here, we propose a simple method to control for possible effects of confounding variables such as age prior to statistical evaluation of magnetic resonance imaging (MRI) data using support vector machine classification (MOBILENET) or voxel-based morphometry (VBM). We compare MOBILENET results for the classification of 80 AD patients and 79 healthy control subjects based on MRI data with and without prior age correction. Additionally, we compare VBM results for the comparison of three different groups of AD patients differing in age with the same group of control subjects obtained without including age as covariate, with age as covariate or with prior age correction using the proposed method. The results suggest that the approach proposed in this work is generally suited to control for confounding variables such as age in MOBILENET or VBM analyses.

K. Franke, G. Ziegler, S. Kloppel, and C. Gaser: The early identification of brain anatomy deviating from the normal pattern of growth and atrophy, such as in Alzheimer's disease (AD), has the potential to improve clinical outcomes through early intervention. Here, we introduce a framework for automatically and efficiently estimating the age of healthy subjects from their T (1)-weighted MRI scans using a kernel method for regression. This method was tested on over 650 healthy subjects, aged 19-86 years, and collected from four different scanners. The framework proved to be a reliable, scanner-independent, and efficient method for age estimation in healthy subjects, yielding a correlation of r=0.92 between the estimated and the real age in the test samples and a mean absolute error of 5 years. The results indicated favorable performance of the RVM and identified the number of training samples as the critical factor for prediction accuracy. Applying the framework to people with mild AD resulted in a mean brain age gap estimate (Brain AGE) score of +10 years.

J. H. Cole: Machine learning analysis of neuroimaging data can accurately predict chronological age in healthy people. Deviations from healthy brain ageing have been associated with cognitive impairment and disease. Here we sought to further establish the credentials of 'brain-predicted age' as a biomarker of individual differences in the brain ageing process, using a predictive modelling approach based on deep learning, and specifically convolutional neural networks (RESNET), and applied to both pre-processed and raw T1-weighted MRI data. Firstly, we aimed to demonstrate the accuracy of RESNET brain-predicted age using a large dataset of healthy adults (N = 2001). Next, we

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sought to establish the heritability of brain-predicted age using a sample of monozygotic and dizygotic female twins (N = 62). Thirdly, we examined the test-retest and multi-center reliability of brain-predicted age using two samples. RESNET brain-predicted ages were generated and compared to a Gaussian Process Regression (GPR) approach, on all datasets. Input data were grey matter (GM) or white matter (WM) volumetric maps generated by Statistical Parametric Mapping (SPM) or raw data.

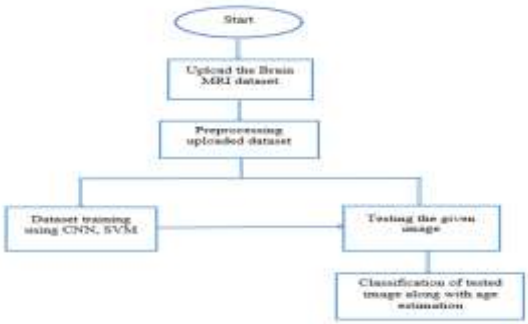
B.A.Jonsson: Machine learning algorithms can be trained to estimate age from brain structural MRI. The difference between an individual's predicted and chronological age, predicted age difference (PAD), is a phenotype of relevance to aging and brain disease. Here, a new deep learning approach is developed to predict brain age from a T1-weighted MRI. The method was trained on a dataset of healthy Icelanders and tested on two datasets, IXI and UK Biobank, utilizing transfer learning to improve accuracy on new sites. A genome-wide association study (GWAS) of PAD in the UK Biobank data (discovery set: N=12378, replication set: N=4456) yielded two sequence variants, rs1452628-T ($\beta=-0.08$, $P=1.15\times10-9$) and rs2435204-G ($\beta=0.102$, $P=9.73\times10-12$). The former is near KCNK2 and correlates with reduced sulcal width, whereas the latter correlates with reduced white matter surface area and tags a well-known inversion.

3. PROPOSED SYSTEM

In our proposed method we are using the cascade network of the deep learning which is a ResNet and also the one of the machine learning algorithms named MobileNet. These algorithms are been used to train the brain MRI images which considered in the three classes as the Normal which is not effected with any disease and the other classes which were effected with Alzheimer's disease (AD) and Mild Cognitive Impairment (MCI). From which we can also find out the ages from the classified images. RESNET and MOBILENET are mainly used for the training of the MRI image dataset, upon where the classification will be performed along with the age estimation.

3.1 ADVANTAGES OF PROPOSED SYSTEM:

- Accurate classification
- Less complexity
- High performance



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3.2 INPUT DESIGN:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc.

Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties −

- It should serve specific purpose effectively such as storing, recording, and retrieving the information.
- It ensures proper completion with accuracy.
- It should be easy to fill and straightforward.
- It should focus on user's attention, consistency, and simplicity.
- All these objectives are obtained using the knowledge of basic design principles regarding −
    - What are the inputs needed for the system?
    - How end users respond to different elements of forms and screens.

Objectives for Input Design:

The objectives of input design are

- To design data entry and input procedures
- To reduce input volume
- To design source documents for data capture or devise other data capture methods
- To design input data records, data entry screens, user interface screens, etc.
- To use validation checks and develop effective input controls.

3.3 OUTPUT DESIGN:

The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report layouts.

Objectives of Output Design:

The objectives of input design are:

- To develop output design that serves the intended purpose and eliminates the production of unwanted output.
- To develop the output design that meets the end user's requirements.
- To deliver the appropriate quantity of output.
- To form the output in appropriate format and direct it to the right person.

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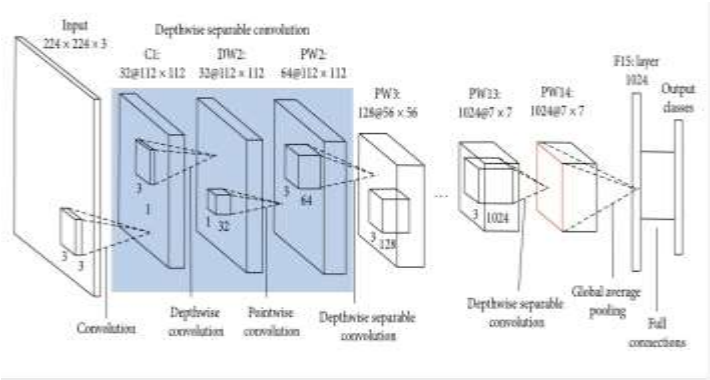
To make the output available on time for making good decisions.

3.3 METHODOLOGY:

MobileNet: As the name applied, the MobileNet model is designed to be used in mobile applications, and it is Tensor Flow's first mobile computer vision model. Mobile- Net uses depth-wise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight dep neural networks. A depth-wise separable convolution is made from two operations.

1. Depth-wise 2. point-wise convolution



MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.
The speed and power consumption of the network is proportional to the number of MACs (Multiply-Accumulates) which is a measure of the number of fused Multiplication and Addition operations.

1 Depth-wise convolution: This convolution originated from the idea that a filter's depth and spatial dimension can be separated- thus, the name separable. Let us take the example of Sobel filter, used in image processing to detect edges. You can separate the height and width dimensions of these filters. Gx filter can be viewed as a matrix product of [1 2 1] transpose with [-1 0 1]. We notice that the filter had disguised itself. It shows it had nine parameters, but it has 6.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

This has been possible because of the separation of its height and width dimensions.

2 Pointeise convolution: Convolution with a kernel size of 1x1 that simply combines the features created by the depth-wise convolution. Its computational cost is $M * N * Df^2$.

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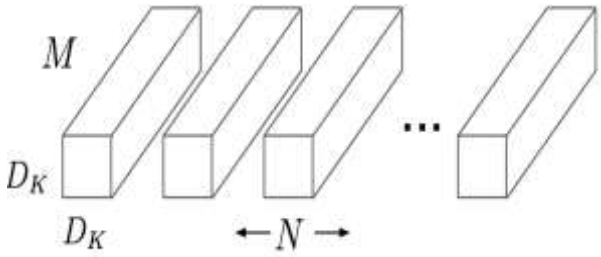
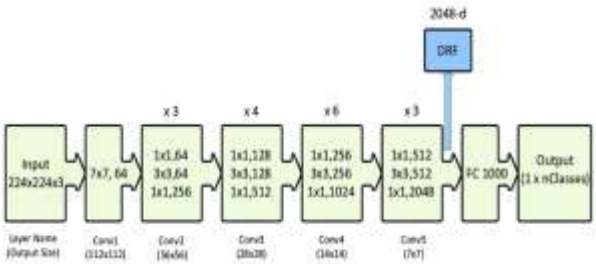


The main difference between MobileNet architecture and a traditional CNN instead of a single 3x3 convolution layer followed by the batch norm and ReLU. Mobile Nets split the convolution into a 3x3 depth-wise conv and a 1x1 pointwise conv, as shown in the figure.

ResNet50:

ResNet50 is a convolutional neural network which has a depth of 50 layers. It was built and trained by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 and you can access the model performance results on their paper, titled Deep Residual Learning for Image Recognition. This model is also trained on more than 1 million images from the ImageNet database. Just like VGG-19, it can classify up to 1000 objects and the network was trained on 224x224 pixels colored images. To sum up, residual network or ResNet was a major innovation that has changed the training of deep convolutional neural networks for tasks related to computer vision. While the original Resnet had 34 layers and used 2-layer blocks, other advanced variants such as the Resnet50 made the use of 3-layer bottleneck blocks to ensure improved accuracy and lesser training time. Keras is a deep learning API that is popular due to the simplicity of building models using it. Keras comes with several pre-trained models, including Resnet50 that anyone can use for their experiments. Therefore, building a residual network in Keras for computer vision tasks like image classification is relatively simple. You only need to follow a few simple steps.

Here is brief info about its size and performance:



ResNet50 Architecture

4. RESULTS AND DISCUSSION

To train the existing and proposed models, this project has used 'Brain MRI image dataset,

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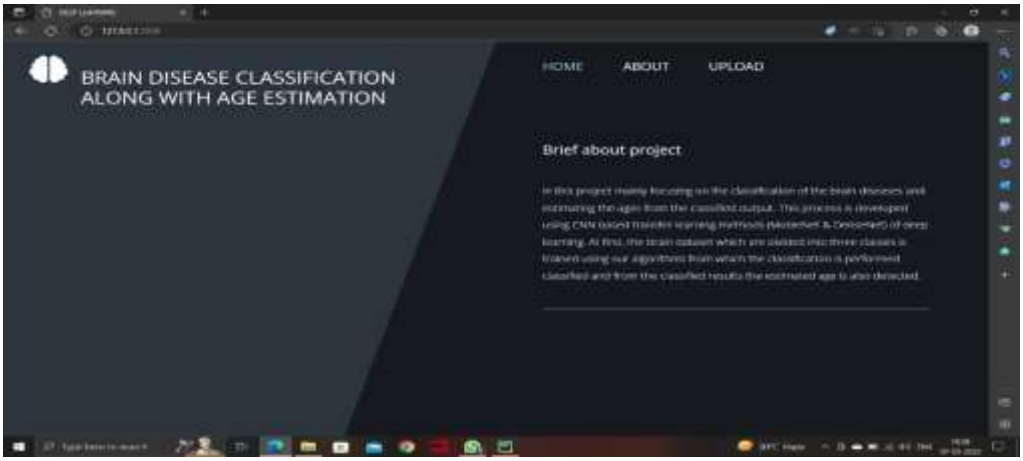
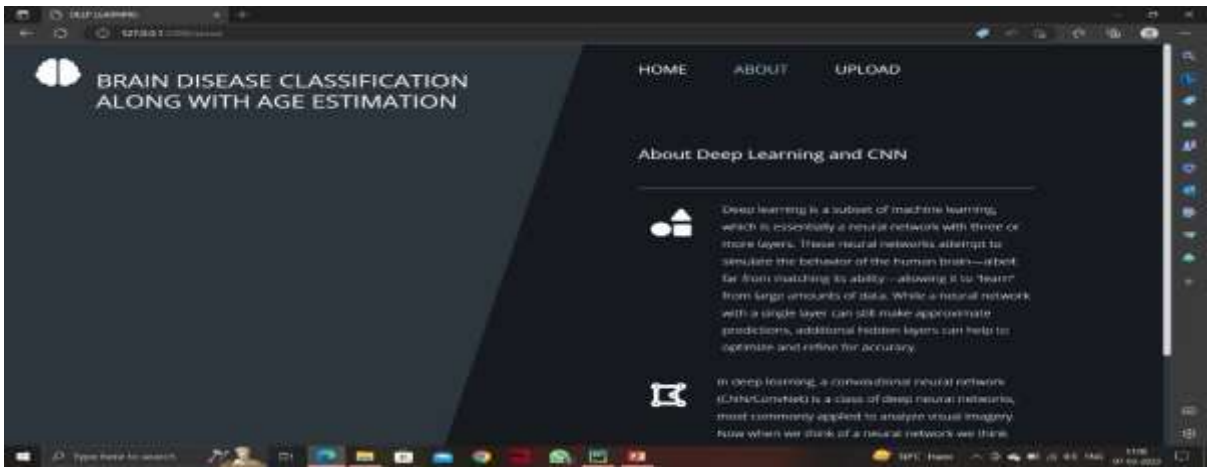
Where input image can be classified according to three types.
They are (mild demented, non-demented, very mild demented).age estimation of patient like(50-70).
We have used above dataset to train all algorithms and evaluate their performance in terms of accuracy.
To implement this project, we have designed following modules.
1) Upload MRI Dataset: using this module we will upload 'MRI Image' Dataset.
2) Pre-process Dataset: dataset often contains brain data and data processing can be
Done by using processing techniques.
3) Preprocessed data can processed by using deep learning techniques. Such as convolutional neural network algorithms.
4) CNN model: using this module we will train CNN algorithm.
5) MOBILE NET Algorithm: using this module we will train MOBILE NET algorithm.
6) RESNET50 Algorithm: using this module we will train RESNET50 algorithm.
7) Comparison Graph: using this module we will plot accuracy comparison between all algorithms.
The initial page for any user is displayed as the following:



After the home page about page is shown as following:



Now user is requested to upload the image:

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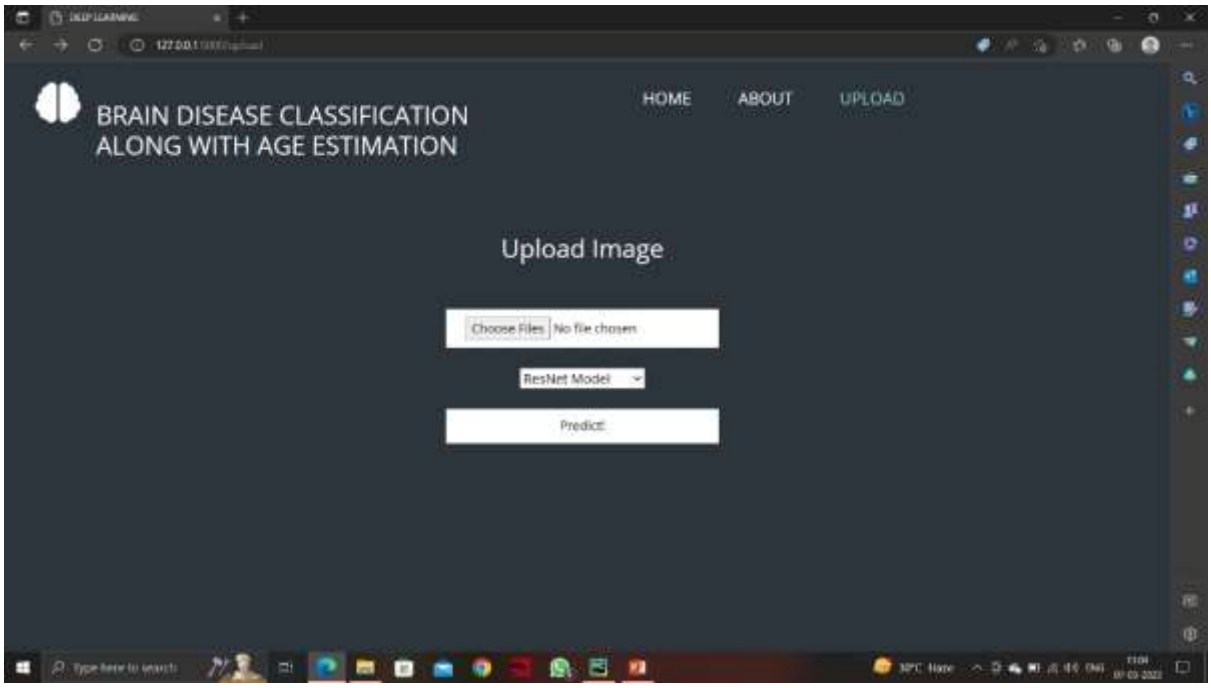
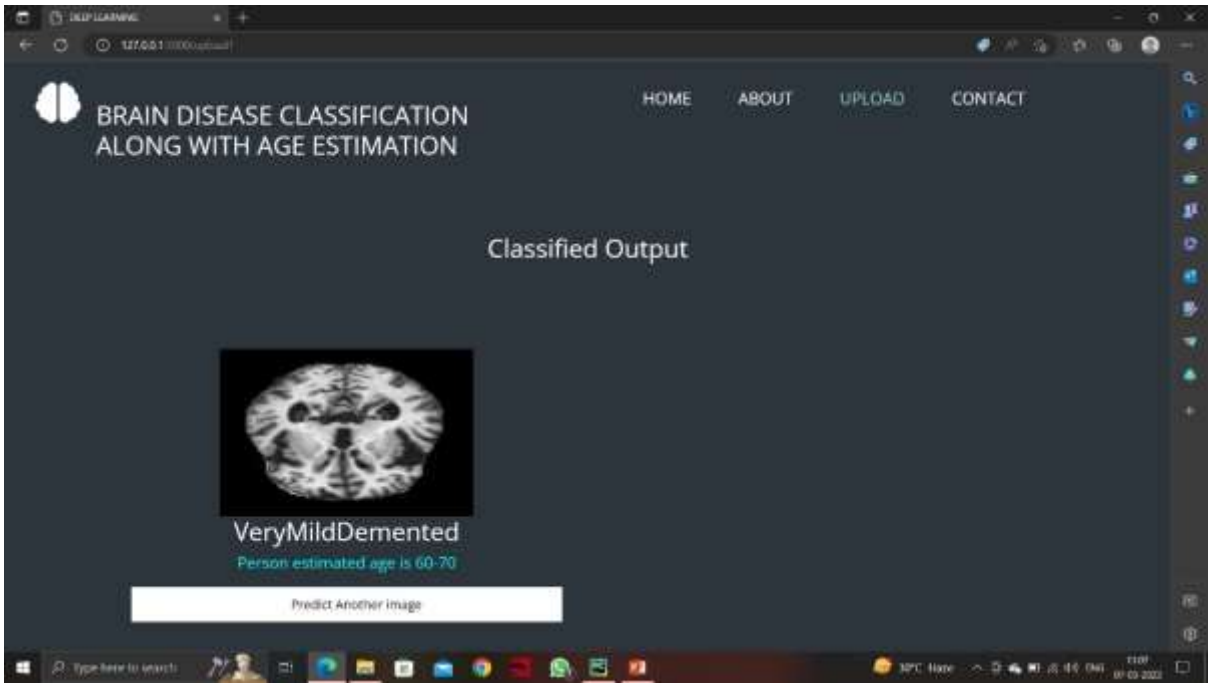


At last the result is shown as following with person estimated age:



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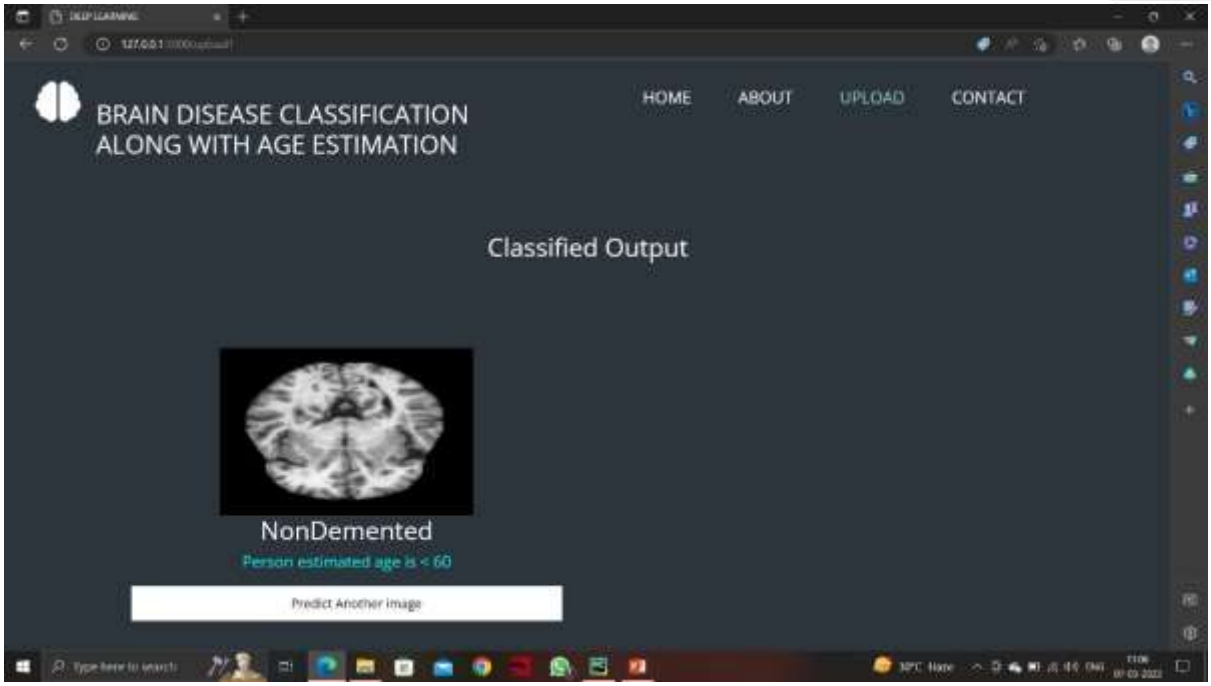
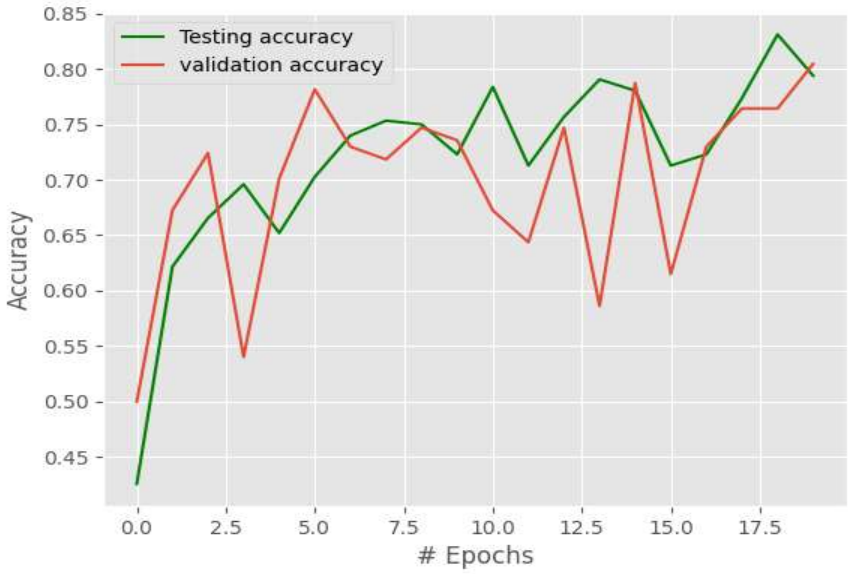


The graphs for this project are testing accuracy:

Resnet accuracy:



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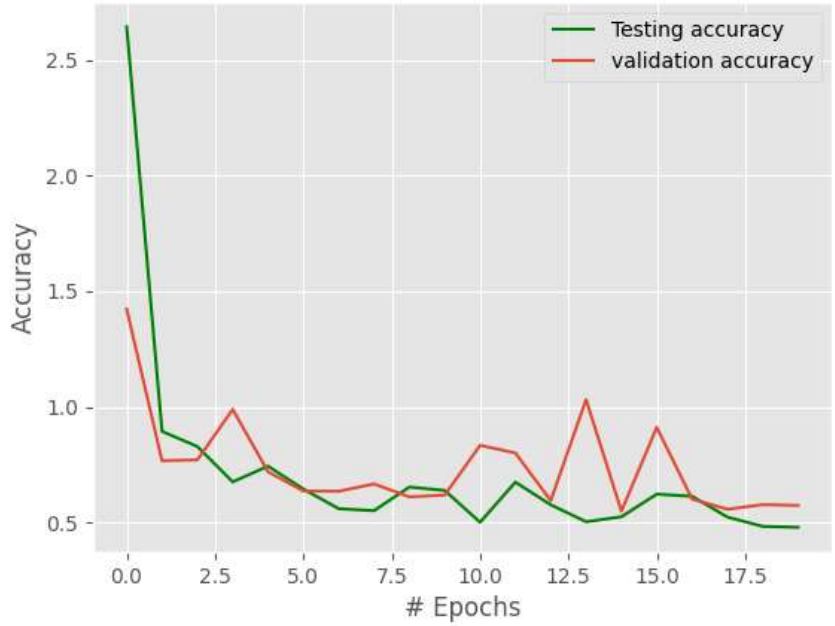
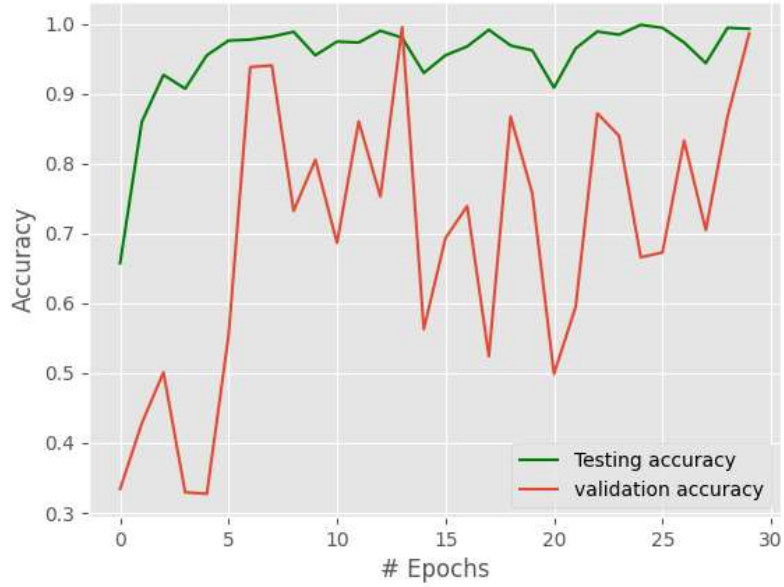
Resnet loss:



Mobilenet accuracy:



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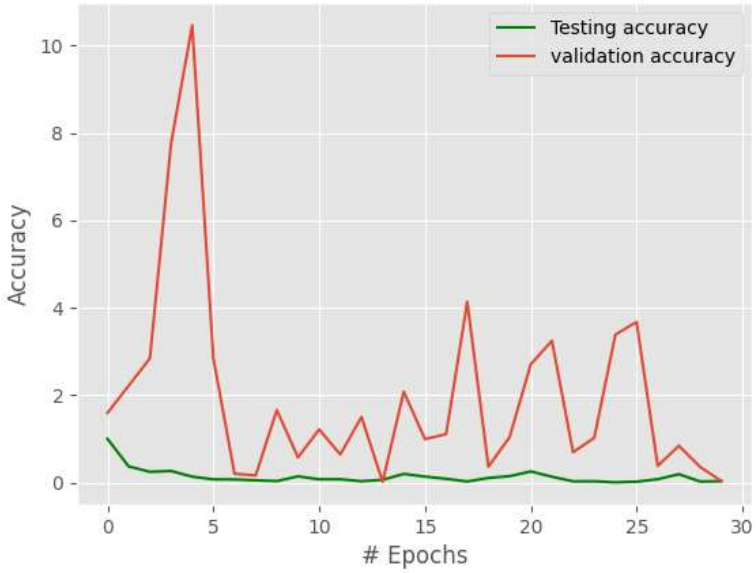
Mobilenet loss:



6. CONCLUSION

Here, we propose a simple method to control for possible effects of confounding variables such as age prior to statistical evaluation of magnetic resonance imaging (MRI) data using support vector machine classification (MOBILENET). Hence, in this proposed method we are using the cascade network of the deep learning which is a Convolutional Neural Network (CNN). This algorithm trained to estimate age from brain MRI images. ResNet50 is a convolutional neural network. Results brain disease classification and along with age estimation.

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