



International Journal of Marketing Management

ISSN 2454 - 5007



www.ijmm.net

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Deep Learning Algorithms for Brain Disease Classification and Magnetic Resonance Imaging Age Estimation

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Abstract—

It is possible to utilize deep neural networks to accurately estimate the chronological age of healthy people using neuroimaging data; this information might then be used as a biomarker to detect diseases associated with aging. A deep learning cascade network called Convolutional Neural Network (CNN) and a machine learning algorithm called Support Vector Machine (SVM) are therefore used in the suggested approach. Using these algorithms, we have been able to train MRI images of the brain into three distinct categories: normal, in which no illness has had an effect, Alzheimer's disease (AD), and mild cognitive impairment (MCI). and age them based on their classifications. The main ways convolutional neural networks (CNNs) and support vector machines (SVMs) are trained on MRI image datasets are for classification and age estimation. Machine learning, convolutional neural networks, deep learning, SVM, magnetic resonance imaging, and age estimate are all related terms. Pydala Bhasha, Indian Institute of Technology (IIT) at Mohan Babu University in Tirupati Contact information: basha.chanti@gmail.com Image Example in Figure 1 No medication can prevent or reverse the progression of an illness, even if some may rapidly lessen adverse symptoms. A heavy burden is often placed on guardians as those affected become more reliant on others for assistance. Factors that contribute to pressure include social, psychological, physiological, and economic factors. Routines might be useful for planning day-to-day tasks and could even lead to better outcomes. Just like the I in figure 1.

INTRODUCTION

The brain disorder known as Alzheimer's disease (AD) often develops and worsens over a lengthy period of time. This accounts for roughly 60% to 70% of dementia cases. The most common early symptom is difficulty evaluating current events. Symptoms of advanced Alzheimer's disease include language difficulties, disorientation (including an increased tendency to get disoriented), mood swings, an obsession with material possessions, a lack of self-esteem, and behavioral problems. Isolation from loved ones and friends is common as a person's health declines. Slowly but surely, the body's systems fail, and death follows. Although there are differences in movement rates, the typical time following discovery is three to nine years. The exact causation of Alzheimer's disease is unknown. Its outcome is influenced by a number of environmental and genetic risk factors. One of the strongest risk factors passed down through generations is an APOE allele. Additional risk factors include a history of brain injury, severe depression, and hypertension. Major contributors to the onset of disease include amyloid plaques, neurofibrillary tangles, and neuronal connections gone wrong. A reasonable conclusion is reached after considering the patient's medical history, psychological evaluation, imaging evaluation, and blood tests in order to rule out other potential causes. Some people mistakenly believe that starting side effects are signs of normal maturation. Evaluation of brain tissue is necessary for a definitive conclusion, however all of the aforementioned must be completed in the hereafter. In 2019, clinical trials investigating these potential outcomes were underway. Advantages in aging, including reduced risk of mental decline and Alzheimer's disease, have been associated with good nutrition, regular physical activity, and strong social connections. There are no proven medicines or healthy improvements that may reduce risk.



RELEVANT STUDY

Effects of breast MRI selective usage on women's decisions to have surgery for operable breast cancer after a recent diagnosis This research looked at the implications of breast MRI in a subgroup of patients with breast illness (obtrusive malignant growth or DCIS) by carefully preparing them for the procedure. Medical professionals turned to magnetic resonance imaging (MRI) when results from more conventional imaging tests were unclear. Patients with recurrent breast cancer who had breast MRIs were included. 2.2 DWI's role in differential diagnosis of endometrial cancer, polyp, hyperplasia, and physiological thickening [5]: We aimed to assess DWI's value in identifying evidence of various common uterine diseases by comparing them to results from contrast-enhanced MRI. 2.3 A free-breathing procedure at 3T for magnetic resonance imaging in radiation for lung cancer Imaging plays a crucial role in radiation therapy. Complex imaging breakthroughs including treatment organization upgrades are necessary for precise growth volume definition. 2.4 Cognitive and affective differences depending on age in Alzheimer's disease (AD) and Parkinson's disease (PD) as they relate to magnetic resonance imaging (MRI) findings [8]: to consider age-related changes in mental and profound cycles related to white matter alterations in patients with PD and AD (PD). 2.5 Alzheimer's disease structural magnetic resonance imaging (MRI) detection with feature ranking and classification error [9]:Based on component placement thinking about recognition for Alzheimer's disease (AD), this work uses primary appealing reverberation imaging (sMRI) data to provide an independent PC-aided indication (CAD) method. Section III: Suggested Approach

Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) are two machine learning techniques that may be used to create the suggested model. First, CNN A convolutional neural network (CNN) takes an image, assigns weights to various parts of the image, and then uses those parts to distinguish between each other. Convolutional neural networks (CNNs) need less data pre-handling in comparison to other deep learning methods. Their work includes recommender systems, picture classification and division, medical image analysis, natural language processing, brain computer interfaces, and time series analysis of financial data, among other areas. CNN variants that have been regularized are multi-facet perceptrons. Figure 2 shows the big picture of how CNNs are designed.

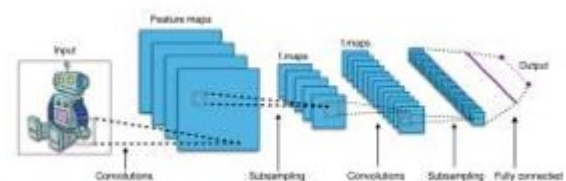


Fig.2 CNN Architecture Extraction

image layout in order to identify a few patterns in the dataset, which necessitates information about picture highlights. Using an ANN for image grouping might become quite expensive in terms of computation because to rather large teachable boundaries. For instance, if we want to train our conventional ANN to identify a dog or a cat from a 50 x 50 image, the teachable bounds on that image would be (50*50). inclination multiplied by two result neurons times 100, 100 image pixels times stored layer times 100, and a propensity to climb towards 2, 50, and 302 Channels are applied when CNNs are being used. Depending on their function, channels may be of many different types. Step One: Select a Dataset. The second step is to get the dataset ready for training. Step 3: Collect Data for Training. Stage 4: Sort Dataset Randomly. The fifth stage is to assign labels and features. Stage 6: Stabilizing X and transitioning markings to 100% data. Step 7: Contemplate CNN's use of split X and Y. The eighth stage is to define, gather, and prepare CNN. Model Model B Accuracy and Scoring in Stage 9. SVM The use of a directed AI method known as Support Vector Machine (SVM) is used while considering both grouping and relapse. Order is the most appropriate phrase, even if we do also make reference to relapse worries. The goal of support vector machine (SVM) technique is to locate

a hyperplane in an N-layered space that clearly organizes data points. SVMs have several uses, including but not limited to: site pages, interruption discovery, face recognizable evidence, email order, quality grouping, and handwriting acknowledgment. This is only one of several reasons why SVMs are used in AI. The validity of both direct and indirect information in characterizing and relapsing is maintained. One benefit of support vector machines is that they can: trained to excel in environments with several layers of resistance. Even when there are more aspects than examples, it is still useful.

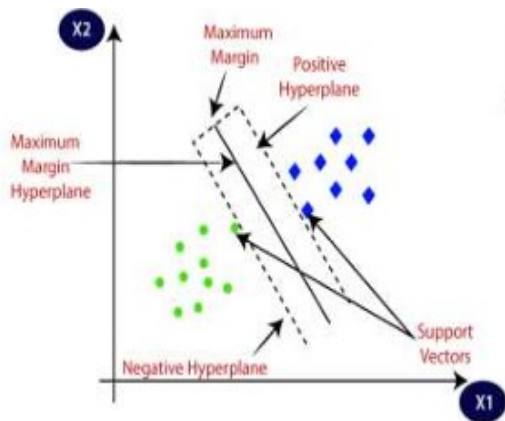


Fig. 3. SVM model

C. A Random Maze Random Forest is the name of a directed AI framework that was built on choice trees. With Random Forest, you may determine whether an email is "spam" or "not spam" and run relapse tests. Irregular backwoods refers to an ordered framework that is followed up around a few selected trees. Using sacking and element arbitrariness to produce each tree, it aims to construct an uncorrelated woods of trees whose gauge via council is more accurate than definite about any particular tree. Since we are dealing with data sets that have subsets, arbitrary woods work well with data sets that contain several layers of information. The aforementioned model prepares faster than choice trees and can easily manage hundreds of features since we are just engaging a portion of the attributes in it.

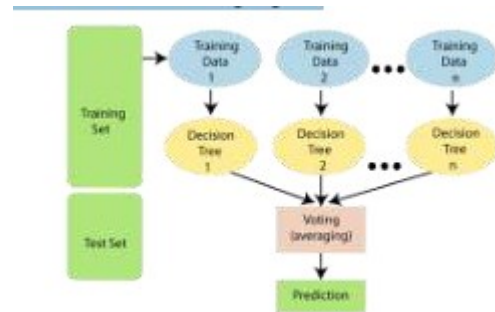


Fig.4 Random forest model

D. Suggested Building Design Normal aging is associated with cortical thinning and intracortical grey matter volume decreases, although these changes happen more rapidly in patients with neurodegenerative disorders like Alzheimer's [1]. The loss of brain tissue caused by Alzheimer's disease (AD) is also more localized than that caused by normal aging [2]. Using magnetic resonance imaging (MRI), it is usual practice to obtain fine-grained cross-sectional pictures of organs such as the brain. An intense magnetic field, radio frequency pulses, and a computer are used in its image-creation process. A faster rate of grey matter volume loss is one symptom of neurodegenerative diseases, which are considered accelerated aging. Magnetic resonance imaging (MRI) computational studies have included a wide range of fields and diseases, including some cancers [3-5]. Section E. System and Modules Start by gathering images of plant leaves; divide them into four categories: healthy, sick, and otherwise unidentified. There are two sets of data: one for training and one for testing; the ratio of test size to training size is 30% to 20%. Pre-processing: Adjusting picture dimensions and cropping them to fit the correct format taking our model training into account. During training, we use a preprocessed training dataset and use machine learning (SVM, Random Forest) and deep learning (CNN, RNN, ResNet) algorithms. Photos that have been classified as having a healthy leaf or a diseased one are shown as a result of our model's classification. Users may evaluate the efficiency of different algorithms after training by seeing their training accuracy. Image uploading: Users have the option to submit classified leaf images. Users like to examine results that take classified photos into account.

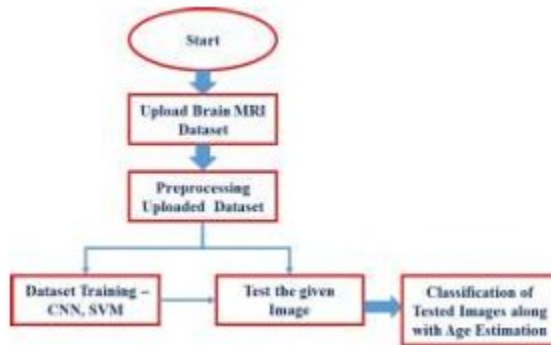


Fig.5. Proposed Architecture

EXPERIMENTAL RESULTS

During the trial, the following outcomes were noted. Figures 6 and 7 show the training accuracy and training loss, respectively, while Figure 8 displays the projected output.

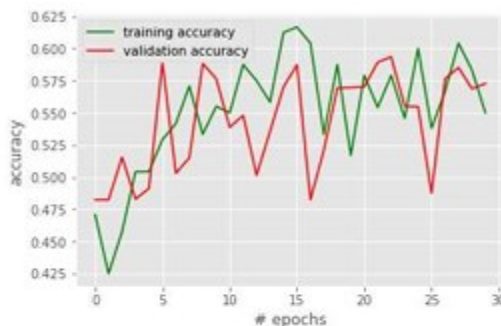
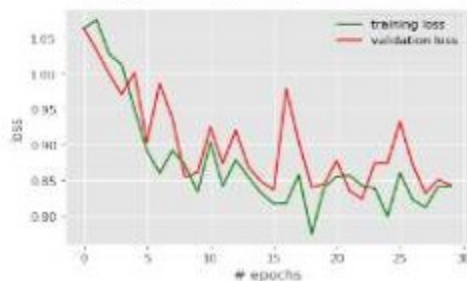


Fig.6. Training accuracy



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1
Accuracy: 0.5728305578231812
predicted image is: Mild Cognitive
Person estimated age is between 60-70
  
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CONCLUSION

We effectively differentiated between normal, Alzheimer's disease, and moderate cognitive impairment in brain MRI images in the aforementioned experiment. The categorization of output also allows for the prediction of age, in addition to wards. Specifically, the aforementioned procedure makes use of SVM algorithms developed using machine learning and CNN algorithms developed using deep learning. Various feature extraction strategies are investigated and used to a dataset consisting of brain MRI images in the aforementioned research. Taking into account the kind of dataset discussed before, it is clear that more characteristics are necessary to get optimal classification results. Even when faced with very little datasets and the dimension curse, the SVM classification technique proves to be successful. To conclude, one may make the case that certain MRI brain scans could be utilized to determine age. Having said that, for a more precise age estimate, it is best to build a model using healthy MRI scans and then predict an individual's age using their MRI picture. Trial results indicated that more robust feature extraction methods might provide more precise results. Another important thing to look at is the method of categorization. Using SVM as a strategy helps overcome the "curse about dimensionality" as indicated in the aforementioned research.

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