

Machine Learning for Early Detection of Alzheimer's Disease from Brain MRI

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Abstract: Recent years have seen an uptick in the use of computed tomography (CT) and magnetic resonance imaging (MRI) scans to create three-dimensional images of the human body for use in medical image processing studies. Immunisations and medical treatment do not work to prevent or treat chronic diseases. Some examples of chronic ailments are asthma, cancer, heart disease, diabetes, and Alzheimer's disease. Alzheimer's disease is a progressive neurodegenerative illness that destroys both memory and personality over time. Without regular checks, diseases like Alzheimer's could not be seen until they've progressed to a fatal level. Millions of individuals throughout the globe are living with Alzheimer's disease, which is a leading cause of death. The first indicator of Alzheimer's disease may be moderate cognitive and/or behavioural impairment, followed by preclinical illness and, ultimately, full-blown Alzheimer's disease. This machine learning model outperforms state-of-the-art medical ailment prediction methods. Most machine learning algorithms for Alzheimer's disease identification are limited to low-dimensional feature spaces because of the sparsity problem. Research in this article examines the feasibility of using several methods such as deep learning, machine learning, and transfer learning approaches to create an early Alzheimer's disease diagnosis.

Keywords: *computed tomography or magnetic resonance imaging scanner, machine learning, deep learning and transfer learning models*

1. Introduction

Researchers in the area of medical image processing have recently begun employing 3D pictures of the human body, often obtained from a computed tomography, or CT, or magnetic resonance imaging (MRI) scanner, for purposes including but not limited to the diagnosis of diseases, the guidance of medical operations like surgery planning, and basic scientific inquiry. Radiologists, engineers, and physicians all employ medical image processing to get a more complete understanding of a patient's or population's physiology. The primary benefit of medical image processing is that it permits a thorough yet non-invasive assessment of interior anatomy. In order to improve patient treatment outcomes, medical equipment and medicine delivery systems, and diagnostics, 3D models of the relevant anatomy may be produced and studied. According to the United States' national centre for health statistics, a condition is

considered chronic if it lasts for three months or more, making illnesses that last for a longer time period chronic diseases. Neither antibiotics nor vaccinations are effective against chronic illnesses, and these conditions do not resolve on their own. As of 1998, 88% of Americans over the age of 65 were living with at least one chronic health condition. The most prevalent chronic illnesses are caused, in large part, by three lifestyle factors: tobacco use, inactivity, and poor nutrition. Asthma, cancer, obesity, heart disease, diabetes, and Alzheimer's disease are just a few examples of chronic illnesses. Most of the population now suffers from at least one chronic illness. In order to foresee the onset of chronic illnesses at an early stage, researchers are developing a wide range of predictive machine learning (ML) algorithms.

Anatomy of Healthy and Alzheimer's Brain

In terms of brain structure, Figure 1 shows the distinctions between a normal brain and one affected by Alzheimer's disease. Alzheimer's disease mostly affects the cerebral cortex, ventricles, and hippocampus. The cerebral cortex, the area of the brain that processes language and information, decreases in Alzheimer's patients, causing them to progressively lose their capacity for learning and memory. The ventricular system, on the other hand, is a network of interconnected brain cavities that generates, channels, and drains the cerebrospinal fluid that cushions and protects the brain

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and spinal cord. Alzheimer's patients have enlarged ventricles, which are filled with cerebrospinal fluid, and

a substantially diminished hippocampus, a brain region essential for the creation of new memories.

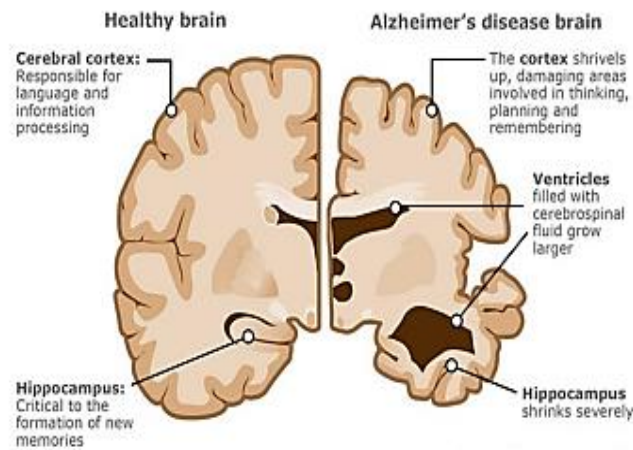


Fig 1. Anatomy of Healthy and Alzheimer's Brain

Diagnosing the illness early on is crucial. A diagnosis of Alzheimer's disease requires a medical examination. Your symptoms and indicators will be assessed by a battery of diagnostic procedures. In order to get additional information regarding patients' symptoms and actions, they may speak with friends and family members. Having Alzheimer's properly diagnosed is crucial. Obtaining a proper diagnosis is crucial to receiving the necessary care, therapy, family education, and future planning. Researchers have begun utilising machine learning models to identify the earliest stages of Alzheimer's disease as the fields of medical image processing and machine learning have advanced.

MACHINE LEARNING APPROACHES TO DETECT ALZHEIMER'S DISEASE

When compared to other illness prediction models in medicine, the machine learning model performs very well. Due to the sparsity issue, most machine learning models are only viable for low dimensional features, which are necessary for detecting AD. There have been new proposals for automated AD prediction using high-dimensional classification and clustering techniques. More effort is being put in at the moment to improve the

machine learning model for Alzheimer's disease detection so that it can be executed faster and more accurately. Both supervised and unsupervised learning may be used to accurately predict the severity of AD. For supervised learning to begin, data must be separated into a "training" set and a "test" set. A dataset is used to teach the classifier, which is then tested on another dataset to see how well it performed. In most cases, the training dataset should include 70–80% of the data, while the testing dataset should contain the remaining 20%. Pre-processing the dataset involves looking for missing values, noisy data, and other anomalies once the training dataset has been created. Then, feature extraction is carried out in order to unambiguously distinguish between the various classes. Then, the performance is enhanced by feature selection. When it comes down to it, the learning process for the identification of AD makes use of supervised models like the support vector machine (SVM), random forest (RF), and decision tree (DT), etc. The performance of the trained classifier may also be evaluated using testing dataset. Figure 2 depicts the whole training and testing procedures used to get supervised learning's prediction findings.

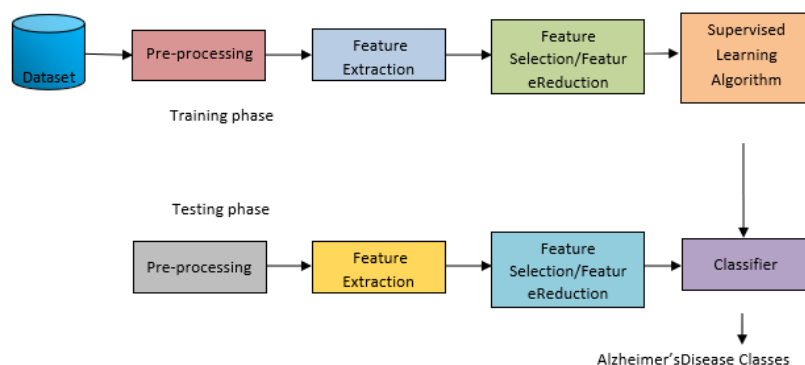


Figure 2 Framework for the Detection of Alzheimer's Disease Using Supervised Machine Learning Model

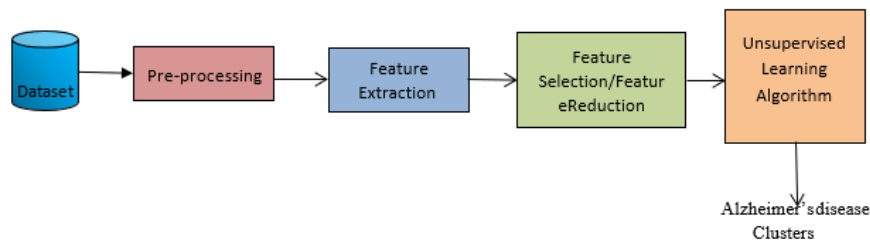


Figure 3 Framework for the Detection of Alzheimer's Disease Using Unsupervised Machine Learning Model

Pre-processing Techniques for Alzheimer's Disease Detection

Researchers are still looking into Alzheimer's disease in hopes of identifying biomarkers that may be used to foretell cognitive deterioration, especially in the earliest stages of the illness. Real-world information is often lacking, loud, and unreliable. The possibility of collecting data with anomalous or inaccurate values is relatively significant due to the exponential rise of data and the rising number of heterogeneous data sources. The only way to get reliable models and, by extension, reliable forecasts, is to start with high-quality data. Therefore, it is essential to ensure the highest quality while processing data.

Pre-processing involves four main steps: cleaning, integrating, transforming, and reducing data. Data cleaning includes procedures like missing value imputation and outlier reduction to enhance the quality of the data. Integrating data is bringing together information from several locations and organising it so that it can be seen by people as a whole. In contrast, data transformation improves the quality of data by modifying its structure or values. However, by using data reduction to cut down on the number of dimensions, the associated computational costs were reduced.

Data cleaning procedures aim to complete the data by adding missing numbers, eliminating noise, locating and removing outliers, and fixing any glaring errors. Filters play a crucial function in smoothing out noise in the visual data. The most common filters used in image processing are the Gaussian filter, the mean filter, the median filter, and the bilateral filter. The image's noise is reduced with the use of a Gaussian filter. Although various methods exist for reducing data, only a select number are routinely used to boost the efficiency of machine learning models. Data reduction methods are used to create a much smaller version of the dataset while still maintaining the original data's integrity. On the other hand, it may be defined as a technique for compressing a high-dimensional dataset into a low-dimensional one without losing any information. Dimensional reduction, data compression, numerosity reduction, discretization, and concept hierarchy are all methods for reducing large amounts of data. In order to

create a more precise prediction model for use in machine learning's classification and clustering tasks, methods for reducing dimensionality are often used.

In the discipline of image processing, segmentation is the most often used pre-processing approach for studying and interpreting pictures. Segmenting an electronic photograph into its constituent parts, or "image segments," simplifies the picture for further processing or analysis. Segmentation, in its simplest form, is the act of classifying images by their constituent pixels. Segmenting an image into its foreground and background components is a kind of picture partitioning. When it comes to the process of picture segmentation, the concept called thresholding is often regarded as the most helpful technique.

Binary thresholding is often regarded as the simplest and most widely used thresholding method. In addition, the adaptable segmentation process is the result of multilayer adaptive thresholding. In the adaptive multilevel thresholding method, the histogram of an image's grey levels is analysed. The grey tags are then divided into at least two groups. Single or multiple criteria govern the cluster creation mechanism. Numerous models for segmentation have been put into place to determine the best threshold settings.

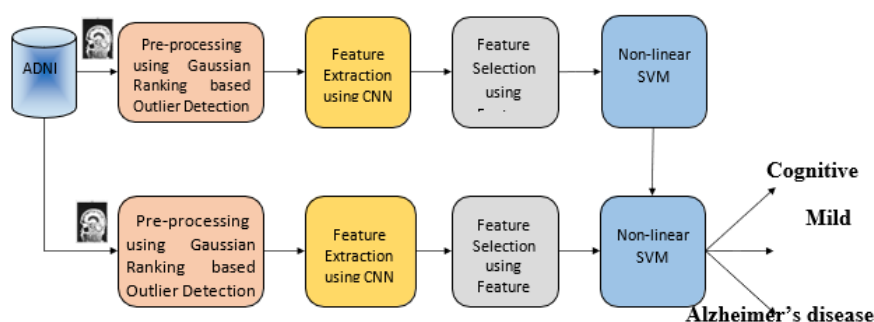
Magnetic resonance imaging (MRI) is a medical imaging technology that creates detailed pictures of the brain by using a magnetic field and radio waves produced by a computer. MRI has demonstrated to be a promising biomarker for predicting the pace of disease development and for early identification of MCI and AD-related alterations. Doctors often utilise MRI scans like this to look for signs of Alzheimer's disease. It's not a simple process to detect alterations in brain structure. The development of machine learning technology allowed for the completion of this mission. Noise in MRI pictures of varying sizes makes it challenging to extract the few meaningful characteristics needed for Alzheimer's disease detection. For this reason, the paper's first research problem is to determine, using MRI images as input, which machine learning model, from among linear discriminant analysis, logistic regression, support vector machine, Naive Bayes classifier, and decision tree, is best suited to detect AD at an early stage based on

various performance metrics. Achieving a suitable hybrid artificial intelligence model which incorporates neural network based feature extraction and traditional classification methods, from CNN with extreme learning machine, CNN with random forest, CNN with decision tree, CNN with K-nearest neighbours model, and CNN with SVM model, to detect AD in its earliest stages based on their performance metrics like accuracy, precision, recall, specificity, error rate, false positive rate, negative predicted value, and F-measure. Thirdly, the article considers the challenge of selecting the most effective deep learning model from among the probabilistic neural network, recurrent neural network, multi-layer perceptron, and DenseNet, and the proposed CNN for early-stage AD detection based on their performance metrics like accuracy, precision, recall, specificity, error rate, false positive rate, negative predicted value, F1-score, etc. Finding a deep transfer learning model that uses AlexNet, GoogLeNet, ResNet, Xception, and VGG16 to detect AD early on based on their performance metrics including precision, recall, sensitivity, specificity, error rate, false positives rate, negative predicted value, and cost is important as the use of audio as a kind of Mel spectrogram image becomes more popular in this field of study.

2. Literature Review

Mangala Shetty et.al (2022) The first clinical indication of AD is selective cognitive impairments, and although there are therapies to alleviate certain symptoms, there is still no cure. Magnetic resonance imaging (MRI) of the brain is used to diagnose Alzheimer's disease in a patient.

Sahaja Dixit et.al (2022) Recent developments in algorithms for deep learning and machine learning have made the biomedical examination of massive amounts of multimodal neuroimaging data more attractive. This article examines four distinct illnesses and disorders



Pre-Processing Using Gaussian Ranking Measure

Gaussian filtering is used to get rid of anomalies and eliminate background noise. Gaussian smoothing operator is a convolution operator in two dimensions that filters out unwanted features. While it has some similarities with the mean filter, it uses a different kernel

affecting the neurocircuitry, with the goal of assisting in their early detection and prevention. Stress prediction for those suffering of stress

DH Chaihra et.al (2021) AD is a neurological illness that causes dementia in patients. There is currently no cure or therapy for AD. Patients with Alzheimer's disease would benefit from early diagnosis so that they may obtain timely treatment. The diagnosis of AD is a common use of statistical and machine learning methods. Deep Learning systems have been proved to outperform humans in a variety of settings.

Neuroimaging Based Alzheimer's Disease Detection System

In order to diagnose Alzheimer's disease early on, a neuroimaging-based approach using a hybrid learning model is presented. Feature extraction, feature selection, and feature categorization are the three main phases of the proposed method. Gaussian ranking based outlier identification is used in pre-processing, as it is in most medical applications, to filter out irrelevant data and eliminate outliers. Convolutional neural networks, a kind of deep learning framework, are used to extract visual features utilised to determine sickness severity during the classification phase. The entropy feature ranking measure is used to narrow down the characteristics to the most relevant for Alzheimer's disease detection. The last step involves using a non-linear support vector machine to categorise the MRI images for Alzheimer's disease prediction based on the features chosen using the aforementioned feature ranking metric. Figure 4 depicts the training and testing phases of the proposed hybrid model for detecting CN, MCI, and AD classes in MRI images from the ADNI dataset, which employs Gaussian-based outlier detection, a convolutional neural network, an entropy-based ranking, and a non-linear support vector machine.

to simulate a Gaussian bell curve. The Gaussian function establishes a probability distribution for noise or data and acts as a smoothing operator. Gaussian ranking metric, which is based on probability values, is employed in this study to filter out noise and anomalies in an MRI scan. A pixel in the MRI picture may have a high or low probability value, depending on the calculations

performed. If the probability value is low, it is assumed to be noise and filtered out of the picture. If the likelihood value is high, it is taken into account. Figure 5

shows the original sagittal MRI picture as well as the output after noise and outliers have been removed by means of the Gaussian filter.

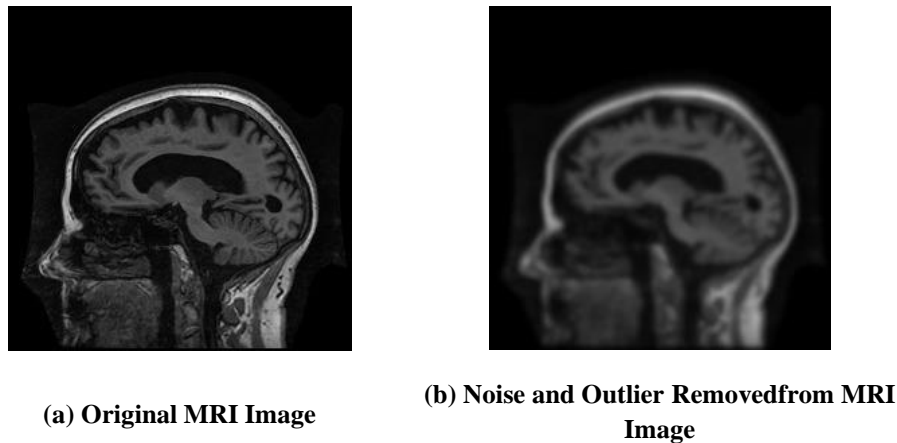


Fig 5. Sample of Pre-Processing Technique

3. Experimental Results

The ADNI dataset is used for the experiments, and the suggested hybrid model is compared to others such as those based on extreme learning machines, random forests, decision trees, and K-nearest neighbours. Accuracy, precision, recall, specificity, error rate, false positive rate, negative predicted value, and F1- score are only few of the statistical output metrics computed for the proposed hybrid model so that its performance may be compared to that of other hybrid machine learning models. While the proposed study uses a support vector machine for machine learning, various models have been tested in its place without altering the features.

Dataset

To diagnose Alzheimer's disease, the suggested model analyses magnetic resonance imaging data. While each MRI picture contains around 170 "slices," only 62 were retrieved for this study because they included enough data for the Mango tool to identify the condition. In this

study, we take into account a total of 7,998 slices related with CN, 8,990 slices associated with MCI, and 4,774 slices associated with AD. In machine learning, the training dataset typically accounts for 70–80 percent of the data utilised, whereas the testing dataset accounts for 20–30 percent. The proposed hybrid model in this study allocates 80% of its time to the training dataset (a total of 17,422 slices) and 20% of its time to the testing dataset (a total of 4,340 slices). The effectiveness of the proposed model is evaluated using a five-fold cross validation procedure to ensure that all samples are independently tested..

Performance Metrics

To measure the efficacy of hybrid models, statisticians utilise the confusion matrix. The confusion matrix obtained for Alzheimer's disease detection using the suggested hybrid learning model is shown in Figure 6 below. The TP, NP, FP, and FN rates are then computed and shown in Table 1 for each of the three classes (CN, MCI, and AD)..

		Predicted Values		
		CN	MCI	AD
Actual Values	CN	1368	28	27
	MCI	99	1456	13
	AD	27	18	1560

Fig. 5 Confusion Matrix of the Proposed Hybrid Learning Model

Class	True Positive	False Negative	False Positive	True Negative
Cognitive Normal	1460	50	122	2816
Mild Cognitive Impairment	1546	110	37	2744
Alzheimer's Disease	1440	32	34	2929

Table 1 True Positive, True Negative, False Negative and False Positive Calculation for Each Class

Class	Accuracy (in %)	Precision (in %)	Recall (in %)	Specificity (in %)	Error Rate (in %)	False Positive Rate (in %)	Negative Predicted Value (in %)	F1-score (in %)
Cognitive Normal	97.20	92.89	96.81	95.94	3.88	4.04	98.16	94.03
Mild Cognitive Impairment	97.52	93.37	92.82	98.65	3.47	1.44	97.28	95.14
Alzheimer's Disease	98.44	97.46	97.32	98.85	1.67	1.26	98.45	97.49
Overall	98.00	95.52	95.52	97.71	3.00	2.32	97.62	95.16

Table 2 Performance Metrics of the Proposed Model for Each Class

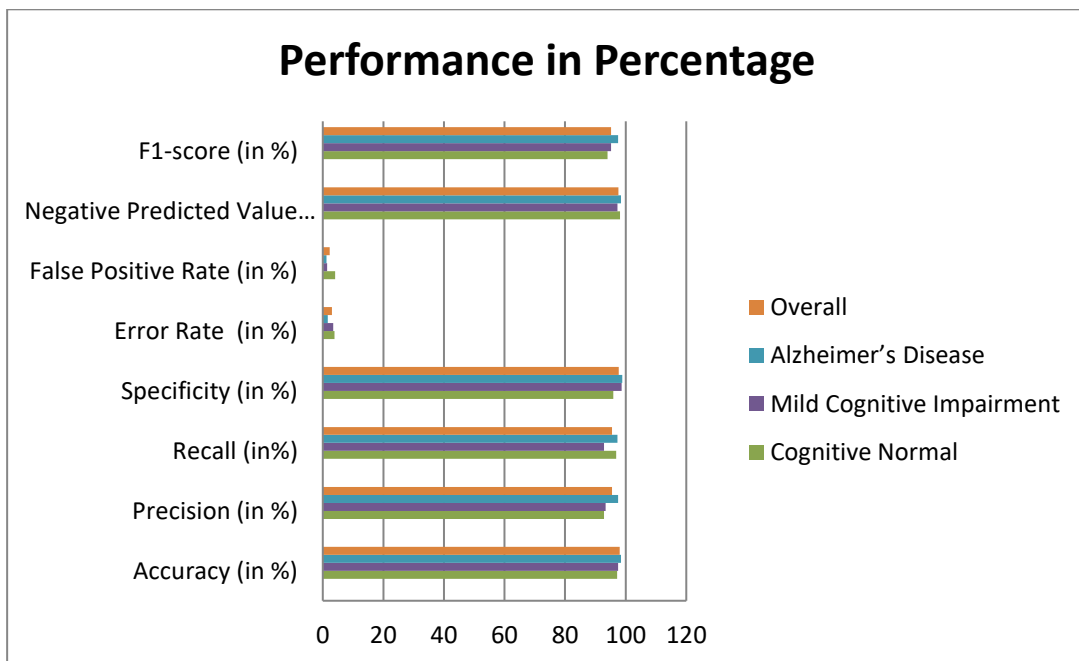


Fig. 6 Performance Comparison of Proposed Machine Learning Model with other Machine Learning Models in terms of Accuracy, Precision, Recall and F1-score

4. Conclusion

This research makes use of a hybrid learning model that consists of a Gaussian filter over reducing noise, an ensemble of convolutional neural network models for the extraction of features, an entropy-based ranking of characteristics metric over feature reduction, and a support vector machine. The goal of this research is to determine Alzheimer's disease in its earliest stages. The hybrid learning model that was developed for the categorization of MRI images taken from the ADNI dataset was evaluated and contrasted with hybrid learning models that already existed. Other machine learning models such as extreme learning machine, random forest, decision tree, and k-nearest neighbour were used in the construction of these supplemental hybrid models. The suggested model had the non-linear SVM component replaced with these other machine learning models. By achieving an accuracy rate of 97.00%, the hybrid model that was developed beat the hybrid learning models that were already in use and were being used as standards. The findings of the experiments also indicate that the suggested hybrid learning model outperforms the alternatives in terms of accuracy, recall, specificity, errors, false positives, negatives projected values, and F1-score. In conclusion, when compared to existing hybrid learning models, the technique that was developed has been shown to be more successful in categorising patients with Alzheimer's disease.

References

- [1] M. Shetty, Deekshitha, M. Bhat and M. Devadiga, "Detection of Alzheimer's Disease Using Machine Learning," 2022 International Conference on Artificial Intelligence and Data Engineering (AIDE), Karkala, India, 2022, pp. 117-120, doi: 10.1109/AIDE57180.2022.10060433.
- [2] S. Dixit, A. Gaikwad, V. Vyas, M. Shindikar and K. Kamble, "United Neurological study of disorders: Alzheimer's disease, Parkinson's disease detection, Anxiety detection, and Stress detection using various Machine learning Algorithms," 2022 International Conference on Signal and Information Processing (IconSIP), Pune, India, 2022, pp. 1-6, doi: 10.1109/ICoNSIP49665.2022.10007434.
- [3] D. Chaihtra and S. Vijaya Shetty, "Alzheimer's Disease Detection from Brain MRI Data using Deep Learning Techniques," 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2021, pp. 1-5, doi: 10.1109/GCAT52182.2021.9587756.
- [4] S. Aruchamy, V. Mounya and A. Verma, "Alzheimer's Disease Classification in Brain MRI using Modified kNN Algorithm," 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC), Gunupur Odisha, India, 2020, pp. 1-6, doi: 10.1109/iSSSC50941.2020.9358867.
- [5] P. Lodha, A. Talele and K. Degaonkar, "Diagnosis of Alzheimer's Disease Using Machine Learning," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-4, doi: 10.1109/ICCUBEA.2018.8697386.
- [6] J. Islam and Y. Zhang, "Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 1962-19622, doi: 10.1109/CVPRW.2018.00247.
- [7] Vijayalakshmi, V., & Sharmila, K. (2023). Secure Data Transactions based on Hash Coded Starvation Blockchain Security using Padded Ring Signature-ECC for Network of Things. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 53–61. <https://doi.org/10.17762/ijritcc.v11i1.5986>
- [8] S. Aruchamy, A. Haridasan, A. Verma, P. Bhattacharjee, S. N. Nandy and S. Ram Krishna Vadali, "Alzheimer's Disease Detection using Machine Learning Techniques in 3D MR Images," 2020 National Conference on Emerging Trends on Sustainable Technology and Engineering Applications (NCETSTEA), Durgapur, India, 2020, pp. 1-4, doi: 10.1109/NCETSTEA48365.2020.9119923.
- [9] S Song, H Lu and Z. Pan, "Automated diagnosis of Alzheimer's disease using Gaussian mixture model based on cortical thickness", 2012 IEEE Fifth International Conference on Advanced Computational Intelligence (ICACI), pp. 880-883, 2012 Oct 18.
- [10] Mr. Dharmesh Dhabliya, Mr. Rahul Sharma. (2012). Efficient Cluster Formation Protocol in WSN. International Journal of New Practices in Management and Engineering, 1(03), 08 - 17. Retrieved from <http://ijnpme.org/index.php/IJNPME/article/view/7>
- [11] DT Bui and ND. Hoang, "A Bayesian framework based on a Gaussian mixture model and radial-basis-function Fisher discriminant analysis (BayGmmKda V1. 1) for spatial prediction of

- floods", *Geoscientific Model Development*, vol. 10, no. 9, pp. 3391, 2017.
- [12] A Kiraly, N Szabo, E Toth et al., "Male brain ages faster: the age and gender dependence of subcortical volumes", *Brain Imaging Behav.* 2016, vol. 10, pp. 901-910.
- [13] X Zhu, Z Lei and H Zi, "A sparse embedding and least variance encoding approach to hashing", *IEEE Trans Image Process*, vol. 23, no. 9, pp. 3737, 2014.
- [14] F. Coppede, E. Grossi, M. Buscema and L. Migliore, *Application of Artificial Neural Networks to Investigate One-Carbon Metabolism in Alzheimer's disease and Healthy Matched Individuals*, 2013.
- [15] P Padilla, M Lpez, JM Grriz, J Ramirez, D Salas-Gonzalez and I. Alvarez, "NMF-SVM based CAD tool applied to functional brain images for the diagnosis of Alzheimer's disease", *IEEE Transactions on medical imaging*, vol. 31, no. 2, pp. 207-16, Sep 2011.
- [16] A. Badnjevic, M. Cifrek, D. Koruga and D. Osmankovic, "Neurofuzzy classification of asthma and chronic obstructive pulmonary disease", *BMC Med Inform Decis Mak BMC Medical Informatics and Decision Making*, vol. 15, no. 3, 2015.
- [17] JC Breitner, "Dementia-epidemiological considerations nomenclature and a tacit consensus definition", *J Geriatr Psychiatry Neurol.*, vol. 19, no. 3, pp. 129-36, 2006.