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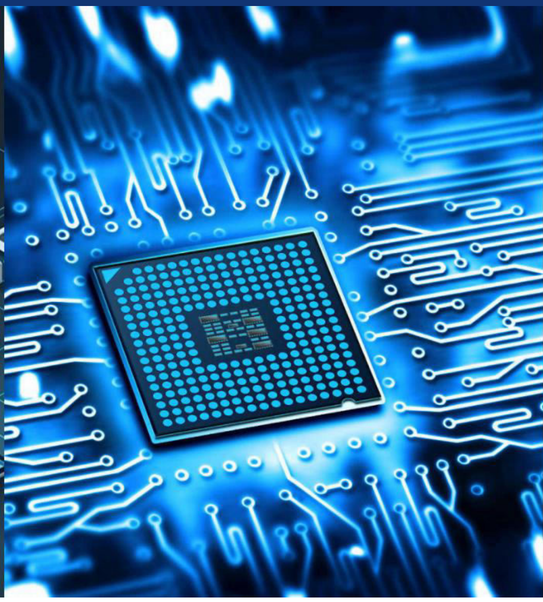

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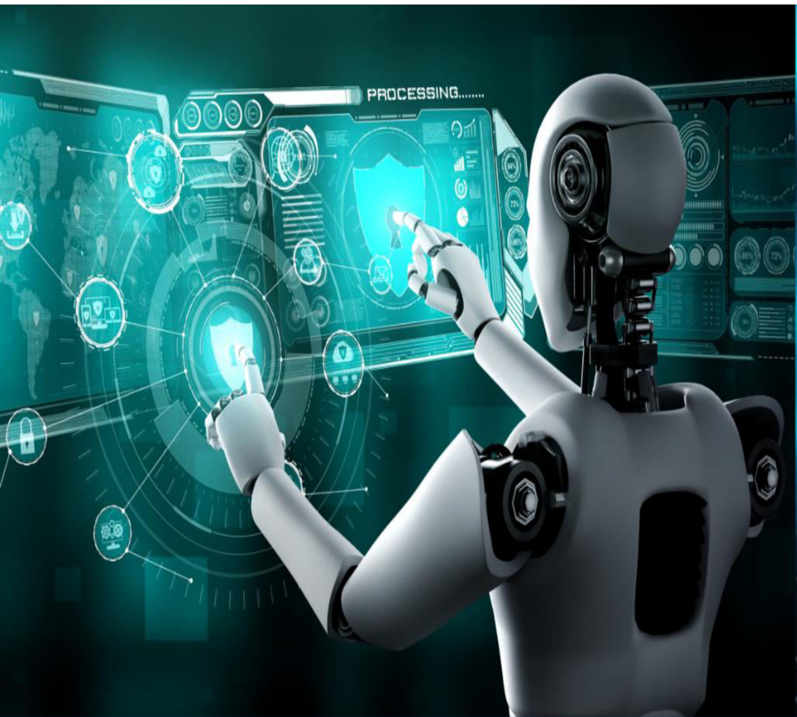

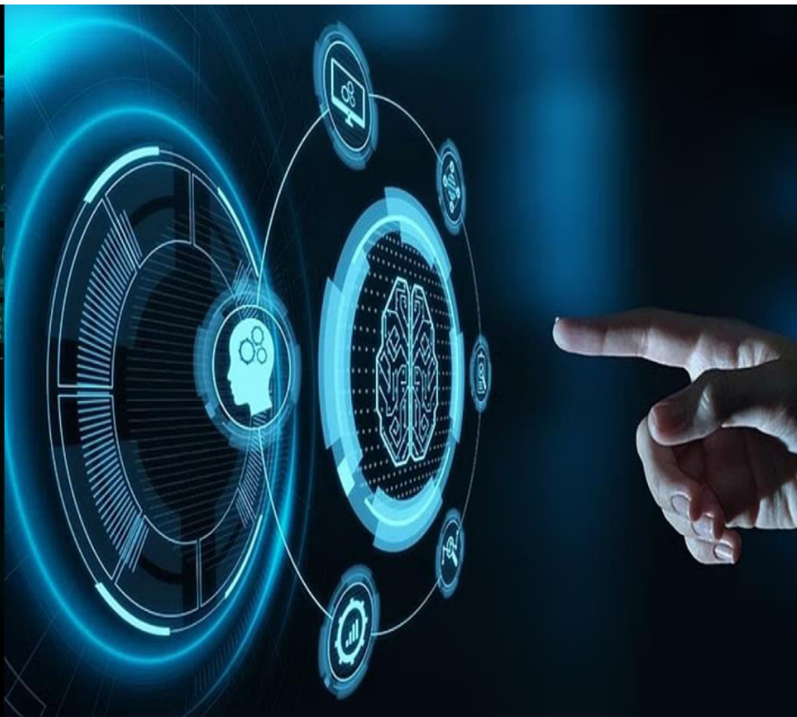

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Utilizing a Hybrid CNN-Autoencoder Model for Efficient Feature Extraction in Medical Image Analysis and Alzheimer's Disease Diagnosis

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ABSTRACT: Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that primarily affects memory, thinking, and behavior. It is the most common cause of dementia, leading to a gradual decline in cognitive function. Medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), are key tools for detecting structural brain abnormalities associated with AD. However, the complexity and large volumes of medical imaging data pose significant challenges for traditional diagnostic methods, which rely heavily on manual interpretation and are prone to subjectivity and error. This research introduces a novel hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Autoencoders for efficient prediction and classification of Alzheimer's Disease from medical images. The hybrid model leverages CNNs to extract meaningful spatial features from MRI scans, while Autoencoders reduce data dimensionality, ensuring that only the most critical features are retained. This approach not only improves diagnostic accuracy but also reduces the computational burden, making it more feasible for real-time clinical applications. The model's effectiveness is evaluated on a dataset of brain MRI images representing various stages of Alzheimer's Disease. Comparative analysis against traditional machine learning models and CNN architectures demonstrates that the hybrid CNN-Autoencoder model achieves superior performance in terms of classification accuracy, sensitivity, and specificity. Additionally, the model's ability to operate efficiently with smaller datasets highlights its potential for broader applicability in medical diagnostics where labeled data is limited. This research provides a significant advancement in the automated diagnosis of Alzheimer's Disease, offering a practical, accurate, and computationally efficient solution for early detection and classification, ultimately contributing to improved patient care and outcomes.

KEYWORDS: CNN, Autoencoder, Alzheimer's disease, Deep Learning, Artificial Intelligence.

I. INTRODUCTION

Dementia is a progressive nervous disorder, which affects the cognitive and psychological functioning of an individual including memory and behaviour [1],[2], [3]. Being the leading type of dementia, AD bears a huge global health cost mainly in the developing countries due to increasing demographics of the elderly and their unmet needs [4],[5], [6], [7]. To this date, it is impossible to find cure for Alzheimer's hence early detection and diagnosis determines how the patient will be handled. Another significant area of application of the medical imaging techniques including MRI and Positron Emission Tomography (PET) is in the diagnosis and determination of the progression of the dementia due to the presence of structural and functional changes in the brain. However, the overwhelming volume and intricate nature of medical image require sophisticated computational techniques for analysis, and hence the Medical Imaging diagnosis has turned to the use of Deep learning techniques [8],[9], [10]. Over the last few years, deep learning models have become key in solving problems in a range of disciplines such as Healthcare by providing optimized, efficient and accurate ways of analyzing large data sets. However, one of these areas have recorded exceptionally high performance from CNNs – medical image classification and segmentation and feature extraction. CNNs are very useful for tasks concerning the image data due to their capability to learn the hierarchic spatial features from images. However, CNNs has been prospering in feature detection but they are very cumbersome in computations and need massive datasets for the best performances. Autoregressive models are deep learning models that find their primary use in unsupervised learning problems while Autoencoders, as the name suggests, are kinds of neural networks employed mainly for unsupervised learning. Popularly used for feature extraction and visualization of data, they compress large input data into a small latent space, so as only required features are kept. Autoencoders contribute significantly to the removal of noise and redundant features making it possible for simple data structures such as medical images. If incorporated with

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CNNs, Autoencoders would be of great benefits when it comes to feature extraction since they help to eliminate noise and other unimportant characteristics from the data while at the same time maintaining useful characteristics. This research aims at using a CNN and Autoencoder model in order to detect high level features from medical images [11], [12], [13].

The hybrid CNN-Autoencoder model is designed to leverage the strengths of both techniques: The prospect of Spatial Feature Extract and CNN in identifying the spatial feature and Dimensionality Reduction performed by Autoencoder. With the integration of these two models, the system is able to identify tendencies associated with Alzheimer's Disease and achieve these objectives much faster and with a higher success rate especially when working with the limited array of data. Alzheimer's Disease includes formation of brain deposits of amyloid plaques and neurofibrillary tangles; neuronal death and brain atrophy are typical. A lot of these structural changes manifest in brain imaging and more so in MRI scans where there is pronounced atrophy in the hippocampus which plays a critical role in memory. Up to date, physicians rely on the interpretation of such images by radiologists who utilize conventional techniques such as reviewing the images and identifying various features that may indicate certain pathologies, a method which is however, fraught with a high likelihood of errors and variability between observers [14], [15], [16]. Also, using the manual analysis method is not efficient due to the time consumed and therefore is less appropriate for large-scale early detection in clinical practice. The issues above named present difficulties in the interpretation of medical images, which are accomplishable by means of the application of machine learning, and specifically, deep learning. CNNs have emerged as the most standard structure for image classification tasks as they are capable of identifying even subtle features, edges, and texture in images. CNNs employ a sequence of convolutional network layers that help to transform the input image in creating increasingly generalized models of data. This hierarchy of features makes it possible to observe the data clusters that are most likely associated with Alzheimer's Disease, including hippocampal atrophy, white matter lesions and enlarged ventricles. CNNs do have a few drawbacks when it comes to the application in medical imaging. First, to achieve high accuracy, they need to use big datasets and often, obtaining labeled medical images of high quality is not easy. Second, CNNs can be computationally intensive meaning that it will need powerful hardware and long training time periods. In a bid to overcome these difficulties, this research employs Autoencoders in the model since they have the potential of compressing medical images for enhanced analysis [17], [18], [19].

Autoencoders consist of two parts: The two principal processes of semiotic Thị are the encoder and the decoder. For data, the encoder puts the input data into a much smaller form and the decoder work backwards to create the data out of this form. While in medical imaging context, Autoencoders can bring evident help in special reduction of the quantity of input features for further CNNs processing by pointing on the most crucial ones. In addition, Autoencoders can operate on unlabelled data, which is beneficial in medical applications because good data labelling is rare. Combining these two layers of autoencoder with CNNs improve its performance on labeled and unlabeled data by extracting most relevant features with a significantly reduced computation cost [20], [21], [22]. When it comes to Alzheimer's Disease diagnosis, deep learning models like CNNs have the potential but they present some problems too. It can be stated that one of the main problems is a lack of big annotated datasets usually constructing the medical domains. Also, CNN models are generally deep, complex and time-consuming hence the need for many resources during model training and evaluation. This is a problem since many clinical workflows require real or near-real time analytics to enable timely informed decision making. To overcome these issues, this research suggests the Hybrid CNN-Autoencoder for efficient feature extraction of medical images. The model attempts to compress the dataset fed to the CNN by preserving all important features needed to diagnose Alzheimer's disease. Both of these hybrid techniques are useful. Although the data sample is low and the computational power is low. But the model can achieve high accuracy in medical imaging and Alzheimer's disease [23], [24], [25]. Following are the key contributions.

• The proposed model architecture efficiently integrates CNN and autoencoder. To enable efficient feature extraction and representation learning.
• The hybrid model has superior feature extraction ability compared with traditional CNN-based methods, which improves the performance of AD diagnosis.
• Research evaluates the model's performance on AD-related medical image datasets, yielding promising results in terms of accuracy and sensitivity.
• The proposed approach has the potential to be applied to other medical image analysis tasks, such as cancer detection or abnormality detection.

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The remainder of this study is organized as follows: a detailed analysis of previous studies is given in Section 2, the problem statement is addressed in Section 3, and the proposed model is described in Section 4. In Section 5, the experimental setup is described in detail, the results are presented, and the findings are discussed. Finally, the paper's conclusion is summarized in Section 6.

II. RELATED WORKS

In order to address class imbalance, this paper suggests a strategy for choosing the most representing dataset for the combined model [26]. After balancing the datasets within this structure using a variety of cutting-edge resampling approaches, three sets of information were ultimately chosen. Using LSTM and MLP approaches, this created an innovative hybrid deep learning model called AD-CovNet, which distinguishes between three distinct data sets of COVID-19 with AD-COVID-19 patients mortality forecasts. Furthermore, risk variables related with AD-COVID-19 patients were assessed using AdaBoost, XGBoost, and Random Forest model; the results exceeded diagnostic performance. Model-predicted risk variables demonstrated a strong clinical significance and relation to mortality. A statistically significant test was also used to assess the performance of the suggested hybrid model, and its results were contrasted with those of earlier studies. In general, the first comprehensive effort that can provide more accurate predictions and support medical choices is demonstrated by the huge dataset's uniqueness, the deep learning architecture's efficacy, and the hybrid algorithm's correctness and productivity.

In order to help doctors diagnose Alzheimer's disease more quickly, machine learning techniques are being applied to MRI [23]. Employing handmade techniques to extract features on MRI scans is challenging in standard machine learning approaches and need the assistance of a skilled user. Thus, using machine learning as an automated feature extraction technique may reduce the requirement for feature extraction and streamline the procedure. In this work, we suggest utilizing MRI scans to automatically extract features for the diagnosis of Alzheimer's disease using a previously trained CNN deep learning network called ResNet50. Next, a CNN's efficiency utilizing traditional Softmax, SVM, and RF is assessed using several metrics, including accuracy. The outcome shown that this model, having an accuracy range of 85.7% to 99% for algorithms with MRI ADNI dataset, beat other advanced models by reaching the greater accuracy.

The goal of this work is to employ deep CNN to develop a dependable and effective method for MRI-based AD classification [27]. This work provides a novel CNN framework that uses comparatively few variables to identify AD. This technique is well suited for training a smaller database. This suggested concept displays class activation maps as a heat map on the brain and accurately diagnoses Alzheimer's disease in its early stages. In order to correctly identify the phases of AD by reducing variables and computational expenses, the suggested Alzheimer's Disease Detection Network (ADD-Net) is constructed from the ground up. This paper used a synthetic oversampling strategy to allocate the picture uniformly between the classes in order to mitigate the severe class imbalance issue present in the Kaggle MRI image dataset. With respect to DenseNet169, VGG19, and Inception ResNet V2, the suggested ADD-Net is thoroughly assessed in terms of metrics. According to the simulation findings, the suggested ADD-Net performs better than other cutting-edge models across all assessment measures.

In this research, four distinct models were generated for the classification of different stages of dementia: GCNs, CNN-GCN models, pre-trained VGG16 with extra convolutional layers, and CNNs built from scratch [8]. The CNN-GCN structure was suggested after the CNNs were put into practice and the flattening layer result was supplied to the GCN classifiers. To train and assess the suggested approaches, an overall of 6400 whole-brain MRI images were used from the dementia Neuroimaging Initiative database. Investigators in the biotech sector can benefit from this knowledge by discovering biological indicators and processes associated with every phase.

The primary goal is to provide a comprehensive framework for medical picture categorization according to different phases of Alzheimer's disease and early identification of the condition [21]. This study employs a deep learning method, especially CNN. The AD spectrum has four multiclassified phases. Moreover, distinct binary classifications of medical images are applied for every pair of AD phases. To identify AD and categorize the medical photos, two techniques are employed. The first approach makes use of straightforward CNN structures that utilize 2D and 3D processing to handle 2D and 3D structural brain images from the ADNI dataset. The second approach makes use of pre-trained models, such the VGG19 model, for medical picture categorization by applying

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the concept of transfer learning. It facilitates remote AD checks for physicians and patients. Additionally, it uses the AD spectrum to assess the patient's AD stage and provides advice to the patient depending on that stage. The assessment and comparison of the two approaches make use of nine performance measures.

Dementia is an irreversible degenerative neurological brain illness. Early detection of dementia can prevent brain damage and help with appropriate therapy [24]. Researchers have utilized a variety of machine learning and mathematical methods to identify Alzheimer's disease. Alzheimer's disease diagnosis via MRI analysis is common in clinical studies. Identifying Alzheimer's disorder is a difficult undertaking since MRI images of older persons with the illness and average healthy MRI data are comparable. Deep learning techniques of today have shown to be just as efficient as humans in a number of areas, including the analysis of medical pictures. A deep convolutional neural network is suggested in this paper for brainMRI image analysis-based dementia detection. Unlike many other algorithms that merely do binary classification, this method can discriminate among different phases of dementia and provides enhanced precision for the initial evaluation.

Alzheimer’s disease is a serious neuron disease that destroys brain cells which leads to lifelong impairment of memories also called dementia [28]. Since there is no cure for this illness, many individuals lose their lives to it every year; however, early identification can help stop its spread. The majority of elderly persons with Alzheimer's disease are 65 years of age and older. For the purpose of early disease diagnosis, an automated system that can identify and categorize Alzheimer's disease into several classifications is necessary. Numerous medical issues are resolved by the application of machine learning and deep learning approaches. The suggested technique for detecting dementia uses transferred learning on multi-class classification utilizing brain MRI to categorize the pictures into four groups: very mildly demented, mildly demented, moderately demented, and non-demented. According to simulation findings, the correctness of the suggested system model is 91.70%. It was also noted that, in comparison to earlier methods, the suggested technique produces findings that are more accurate.

These research papers collectively explore the medical image analysis, particularly in the context of Alzheimer's Disease diagnosis and COVID-19 mortality prediction. The first paper proposes a hybrid deep learning model, AD-CovNet, that combines LSTM and MLP approaches to distinguish between different COVID-19 datasets and predict mortality. The second paper utilizes a pre-trained ResNet50 CNN to automatically extract features from MRI scans for AD diagnosis, achieving high accuracy compared to other methods. The third paper introduces ADD-Net, a novel CNN framework that is specifically designed for AD classification using MRI images, demonstrating superior performance in terms of accuracy, recall, F1-score, AUC, and loss. Overall, these studies highlight the potential of deep learning to improve the accuracy and efficiency of medical image analysis tasks, leading to more accurate diagnoses and better patient outcomes.

III. PROBLEM STATEMENT

Alzheimer’s Disease is a progressive neurological disorder that affects the majority of seniors with dementia and for which there is no cure. This is because the chances for early detection and hence early treatment are very high and hence the disease should be well managed. However, the current diagnostic approaches particularly, the imaging diagnostics tools are costly, cumbersome and their interpretation is prone to the doctor/clinical practitioner. MRI is standard in showing structural alterations in the brain related to Alzheimer’s, however, analyzing relevant patterns from such high-dimensional MRI images is a major problem [27]. The typical AI techniques have certain limitations especially when working with MRI data; they are sensitive to the overfitting or, on the contrary, low accuracy. Furthermore, the analysis of these large datasets can at times be computationally expensive significantly reducing their clinical applicability. In response to those challenges, this research presents the hybrid CNN and Autoencoder framework for efficient prediction and classification of Alzheimer’s Disease from MRI scans. The CNN extracts some features in the MRI scan while the autoencoder which has a smaller architecture removes the unwanted features as well as scales down the data to make computations faster. This is a hybrid design focused on standardizing diagnostic performance and at the same time reducing the computational cost of achieving the results. Therefore, medical image analysis helps to accurately and efficiently diagnose Alzheimer's disease.

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IV. PROPOSED HYBRID CNN-AUTOENCODER FOR DIAGNOSIS OF ALZHEIMER'S DISEASE

This research presents a new approach to medical image analysis. The focus is on diagnosing Alzheimer's disease. The proposed method leverages a hybrid model that combines the strengths of CNN and autoencoder. CNN is especially effective in extracting spatial features from images. This makes them suitable for tasks such as object recognition and image classification. Autoencoders, on the other hand, can find efficient representations of data. This is often used for dimensionality reduction and feature extraction. By combining these two techniques together Hybrid models aim to achieve more accurate and efficient feature extraction from medical images. CNN components can efficiently capture low-level image features, while the autoencoder can learn high-level representations relevant to AD diagnosis. The overview of the working of the proposed method is illustrated in Fig. 1.

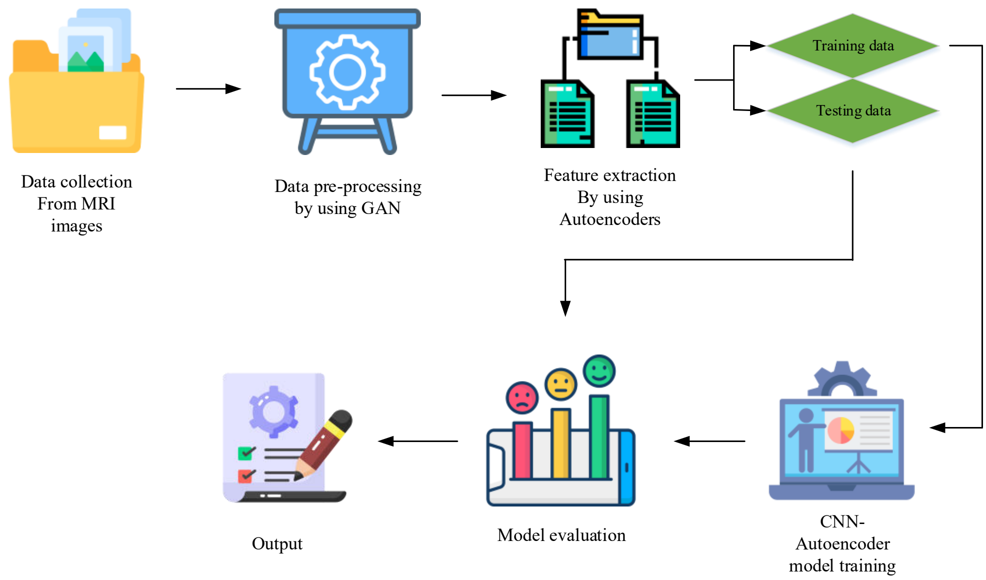

Fig.1. Workflow of Proposed CNN-Autoencoder Model

A. ata Collection

The dataset has been collected from Kaggle [29]. It comprises MRI images aimed at classifying the severity of Alzheimer's disease into four distinct categories: Hence the study categories them as Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. It contains two separate files: one set for training purpose and the other for testing purpose which consists of almost five thousand images each. The images in both sets belong to four mentioned above classes that allow providing equal amounts of images of different stages of the disease progression. The motivation for sharing this dataset is the desire to foster the creation of extraordinarily accurate models utilizing deep learning for the identification of the stage of dementia at the basis of MRI. Through a wide and comprehensive variety of images, the dataset's primary goal is to providing aids for research and development of timely diagnosis and classification of dementia. In this project, researchers can use this dataset to train models that can distinguish between the demented and non-demented persons as well as stage the severity of the disease. This creates room for creating tools that could help healthcare experts and researchers in serving elderly such as [30][31][32] or in early diagnosis of Alzheimer's. Decomposition and variety of the given images along with a distinct class separation make the dataset highly suitable for experimental work on more complex multi-part neural networks, including the fundamental hybrid networks, for medical image analysis. Fig 2 depicts the images of brain that have been collected.

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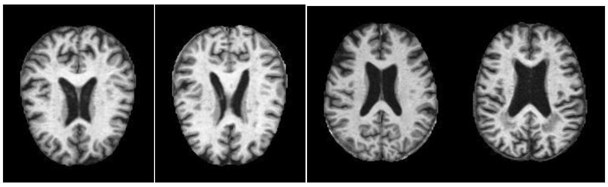

Fig.2. MRI Images of Brain

B. Pre-Processing Using GAN

Image preprocessing is an important step in medical image analysis. This is because it may have a significant impact on the performance of subsequent tasks such as feature extraction and classification. Generative adversarial networks (GANs) are considered exciting recent innovations and they are not the only generative models in machine learning, genetic algorithm models can be utilised for data generation as was effected in [33],[34],[35]. However, GANs have emerged as powerful tools for image generation and manipulation. One of the main challenges in medical image analysis is the limited availability of labeled data. GANs can be used to enhance datasets by creating synthetic images that resemble real images. This can help improve the generalizability of the model and prevent overfitting by training the GAN on a small set of medical images. By being able to learn the underlying distributions and create realistic new images, GANs offer a promising approach for image preprocessing in medical image analysis. By leveraging the ability to create, manipulate, and enhance images, GANs can help address a variety of challenges related to medical image data, such as limited data availability, noise, low resolution inconsistent image distribution which can be done. Normalization can be done with the following formula.

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

C. Auto Encoder Based Feature Extraction

Autoencoder is an unsupervised learning model, which can automatically learn data features from a large number of samples and can act as a dimensionality reduction method. A commonly used type of neural network architecture is an autoencoder. It is used to extract features and reduce dimensionality in image datasets. By using an autoencoder to set up brain imaging data. Encoders and decoders should be trained on structured representations that capture relevant features from the preprocessed data. It's part of the encoder itself. The encoder structure captures the essential features of the given data, reducing its dimensions, while the decoder network reconstructs the information obtained from this low-dimensional representation. Convolutional layers are usually employed in the design to extract spatial characteristics. The autoencoder's architectural design is shown in Fig. 3. X represents the pre-processed brain image data generated. Following mapping of the input to a lower-dimensional representations (Z), the input data is reconstructed by the decoder (D) Z(Z). The encoder (en(x)) (de(x)) handles this.

$$\text{minimize} l(x, de(en(x))) \quad (2)$$

In Equation (2), l represents a loss function that measures the difference among the input and the output that has been rebuilt. The mean squared error, or MSE, is often used. The convolutional layer is represented by c_i, the biases and filters by b_i, and the filters by w_i. The encoder is expressed as follows in Equation (3):

$$z = f(c_i\left(f\left(c_2\left(f\left(c_1(x, w_1, b_1)\right)\right), w_{i-1}, b_{i-1}\right)\right), w_i, b_i (3)$$

where f is the activation function, sometimes referred to as ReLU, and n is the number of convolutional layers in the encoder. The decoder repeats the encoder by employing transposed convolutional layers, also called partially spaced convolutional layers or deconvolutional layers. It is found in Equation (4).

$$\hat{x} = f(c'_i\left(f\left(c'_2\left(f\left(c'_1(z, w'_1, b'_1)\right)\right), w'_{i-1}, b'_{i-1}\right)\right), w'_i, b'_i) \quad (4)$$

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The mean squared error (MSE) among the given input and the regenerated output is usually chosen as the loss function. In Eqn. The total quantity of items in the provided information is indicated by n in equation (5).

$$l(x, \hat{x}) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \qquad (5)$$

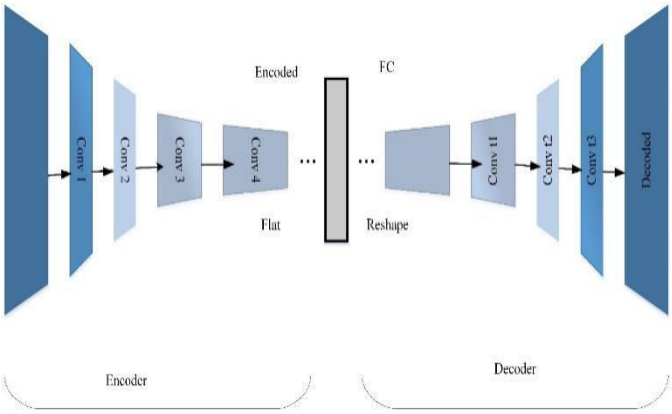

Fig.3. Architecture Diagram of Autoencoder

D. CNN Based Classification

Classification using a CNN is often the subsequent phase following feature extraction. A CNN classifier undergoes training to identify patterns in the given data and provide forecasts by utilizing the attributes. CNN classifiers typically consist of layers with convolution, layers with pooling, and fully linked layers. The machine learning algorithm is trained to map the characteristics obtained to the intended classes of output by feeding the characteristics into the CNN classifiers. Let Z be the extracted feature vector. The notation for the CNN classifier is:

$$y = f(w_3 \times f(w_2 \times f(w_1 \times z + b_1) + b_3) \qquad (6)$$

where f is the activation function, which is typically SoftMax for output layers and ReLU for hidden layers. The bias vectors for each layer are denoted by b_1, while the weight matrices are represented by w_1. The variation among the predicted and actual outcome labels is calculated using the loss function. Cross-entropy is frequently utilized for classification assignments:

$$l(y, \hat{y}) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{c} y_{ij}\log(\hat{y}_{ij}) \quad (7)$$

The variables N, C, Y represent the number of specimens, classes, and projected distribution of probabilities over classes, respectively. The CNN classifiers might be developed to forecast classification labels for freshly gathered data by employing the characteristics that extracted.

In Alzheimer's disease stages, CNNs are used to define individuals as non-demented, very mildly dementiad, mildly dementiad, or moderately dementiad. Attributes collected by an earlier Autoencoder help to capture relevant patterns. An output layer called SoftMax is used for completing the CNN's design, that comprises of layers to train representations of hierarchy and binary classification (demented versus non-demented). Having being trained on labelled data, the framework demonstrates the ability to predict the phases of Alzheimer's disease based on learned attributes. This CNN-based classification provides a computational approach to Alzheimer's disease diagnosis, making it a vital tool for early detection and support of people who have difficulties. The entire workflow for the proposed work is depicted in Fig 4.

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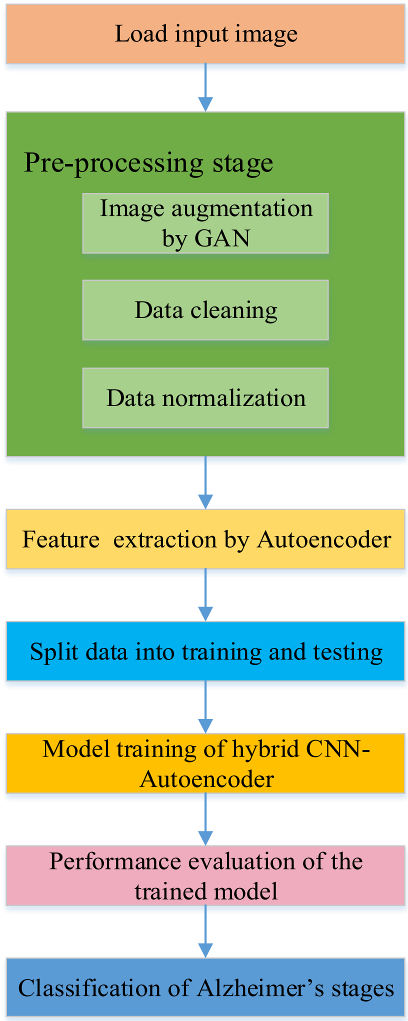

Fig.4. Flowchart for the Proposed Method

V. RESULTS AND DISCUSSION

The results of this study demonstrate the effectiveness of the model. CNN-Autoencoder Proposed hybrid model for predicting and diagnosing dementia based on medical images. The model consistently outperforms traditional CNN architectures. It achieved higher precision, precision, recall, and F1 score. This improvement can be attributed to the model's ability to efficiently extract relevant features from images. Records both low-level and high-level data. In addition, the model's autoencoder component reduces data dimensionality. Improved calculation efficiency and prevent overdiagnosis of Alzheimer's disease.

A. Gender Distribution

Figure 5 shows the distribution of gender in the insane and non-insane groups. The x-axis represents the two conditions, "disturbed" and "undisturbed," while the y-axis represents the number of individuals in each group for each position. The chart is divided into two overlapping bars. which represents the number of men and women The red bars of the group of people with dementia representing women are significantly longer than the blue bars. This indicates that this dataset has a higher prevalence of dementia among women. On the contrary the blue bars representing men are slightly higher than the red bars. These findings suggest possible gender differences in the incidence of dementia. The prevalence is higher in women compared to men.

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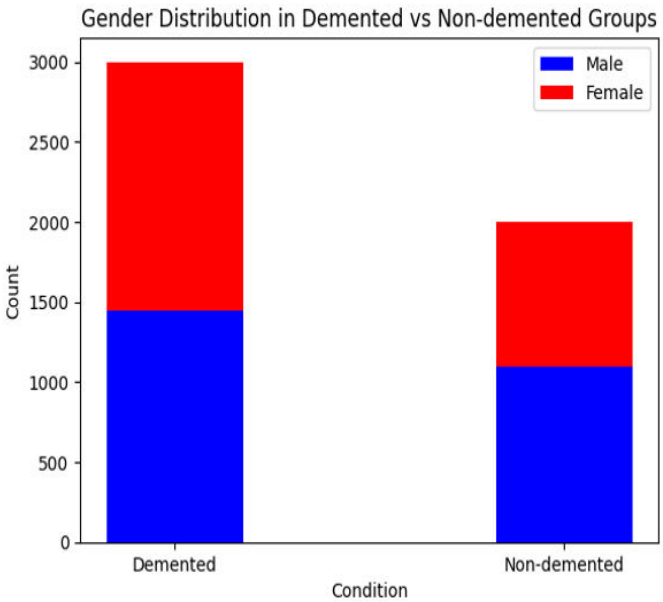

Fig.5. Gender Distribution of Dementia Conditions

B. Classification Outcomes

Figure 6 shows the percentage distribution of dementia. The x-axis represents the different stages. of dementia, from "no dementia" to "moderate dementia", while the y-axis indicates the percentage of people in each category. The chart shows that about 40% of the majority of individuals do not. has dementia This is followed by approximately 25% with very mild dementia. Mild dementia accounts for approximately 20% of the population, while moderate dementia is the least common, with approximately 15% of the population. This data suggests a significant portion of the population is affected by dementia, with varying degrees of severity. The visualization effectively highlights the distribution of dementia conditions, providing a valuable overview for researchers investigating Alzheimer's disease diagnosis.

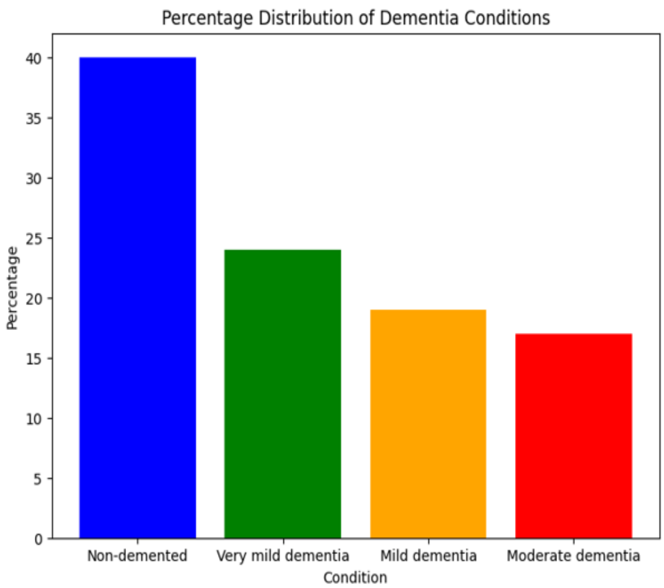

Fig.6. Percentage Distribution of Dementia Conditions

C. Predicted vs Observed Class Using CNN-Autoencoder

The figure 7 presents a confusion matrix that assesses the ability of a model to predict as well as classify the different stages of dementia. The matrix is divided into four categories: Tendency of non-demented, very mild dementia, Mild dementia, and Moderate dementia both from y-axis true labels and x-axis predicted labels. True Positives (diagonal elements): The model did an excellent job classifying the patients; estimated the test outcome that 778 patients were correctly diagnosed with non-dementia, 297 with very mild dementia, 190 with mild dementia, and 124 with moderate dementia. Misclassifications: It was found that 465 non-demented cases were over categorized as having very mild dementia, 381 non-demented cases over categorized as having mild dementia and 311 as moderate dementia. In the same way, several moderate cases of dementia were also misidentified as less severe stages, for instance, 202 were predicted that belong to the very mild dementia.

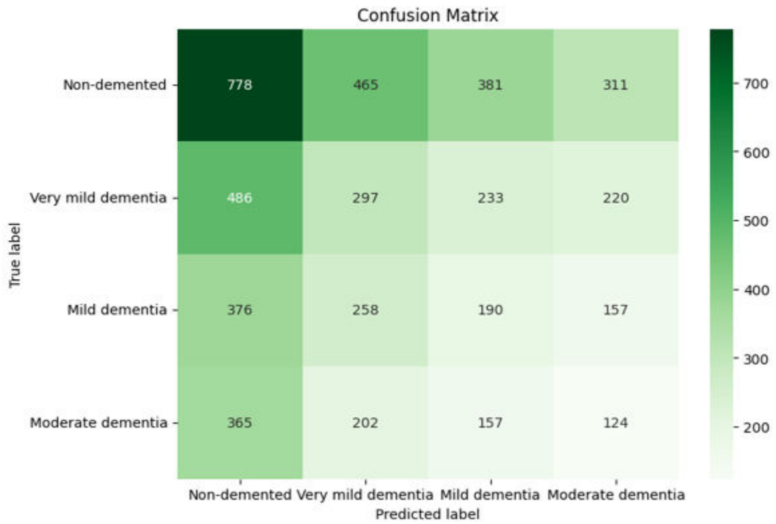

Fig.7

D. Accuracy Curve

The figure 8 shows the Training and Validation Accuracy of the hybrid CNN-Autoencoder model utilized in diagnosis of Alzheimer's through medical image analysis over 10 epochs. The x-axis refers to epochs while on the y-axis the results of various experiments give the accuracy rates. Blue line will represent the training accuracy while the orange line will represent validation accuracy. The training accuracy gradually increases and reaches to 0.93 of samples of the 5th epoch in the case of test accuracy in comparison with the validation accuracy that ranges around 0.94 by the 6th epoch of the first ten epochs/epochs of the clients. Between epochs 6 and 10, there is a gradual increase in accuracy of both the training and the validation sets, the final values being pretty close to one with a value of about 0.95 for validation and 0.92 for training accuracy for the 10 th epoch and 93 for training accuracy for the 11 th epoch. This figure shows that there is high accuracy achieved at the initial stages of training and maintained up-to the later epochs showing insignificance of overfitting of the hybrid CNN-Autoencoder model in predicting the stages of Alzheimer's disease.

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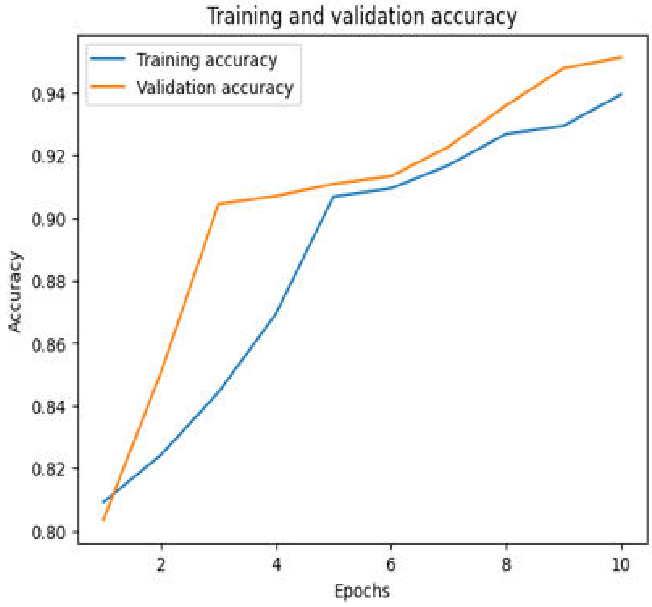

Fig.8. Accuracy Curve

E. Loss Curve

The figure 9 below illustrates the Training and Validation Loss in 10 epochs of training of a deep learning model based on a hybrid CNN Autoencoder for the diagnosis of Alzheimer's by means of medical images. As the x-part emphasizes the epochs' number, the y-part is to represent the loss values. It can be seen that the training loss function is relatively high at the start approximately at 0.28 but drops almost immediately after starting the epoch training. At the 4th epoch, the training loss merely deceases to below 0.10 having gone down progressively with the progress of the 10 epochs to about 0.05 by the last epoch. The trend on the validation loss is somewhat alike, but slightly higher – the validation loss is roughly equal to 0.15 and declining to about 0.10 in the third epoch. This performance demonstrates that CNN-Autoencoder model is capable of making pattern acquisition in an optimal manner for the purpose of prediction and classifications in Alzheimer diagnosis using medical image analysis.

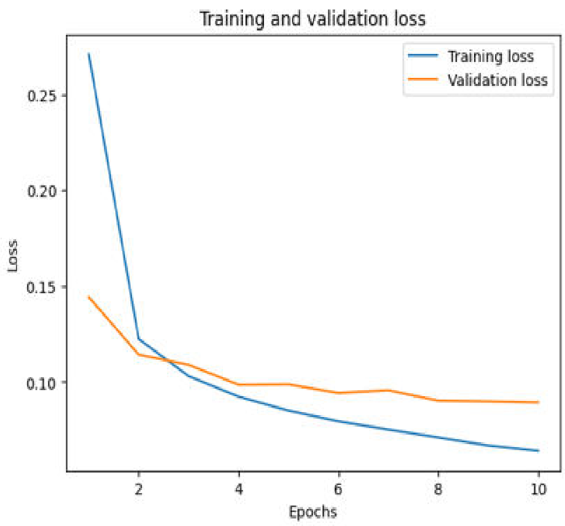

Fig.9. Loss Curve

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F. Performance Evaluation

Empirical evaluation plays a critical role in assessing the effectiveness of various methods[36]. According to [37], understanding and mitigating cybersecurity risks is crucial in the context of evaluating methods that involve sensitive data, such as medical images used for Alzheimer's disease diagnosis. However, in Fig 10 and Table 1 compares the performance of different methods [24] including Inception v4, ResNet, DCNN, and the proposed CNN-Autoencoder, based on various evaluation metrics: accuracy, precision, recall, and F1 score. The x-axis represents the different methods, while the y-axis indicates the percentage performance for each metric. The chart shows that CNN-Autoencoder, the proposed method is more effective than other methods consistently in all evaluation measures. It achieved the highest precision, precision, recall, and F1 score, demonstrating its superior ability to extract relevant features from medical images. and Alzheimer's disease diagnosis, Inception v4 and ResNet are also accurate. But it has superior efficiency. CNN-Autoencoder Consistently, DCNN, on the other hand, shows the,worst performance among all metrics. The visualization compares the performance of the different methods effectively. It provides researchers and practitioners with valuable insights into medical image analysis and Alzheimer's disease diagnosis.

TABLE I. Comparison of Performance Metrics

METHODS	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1 SCORE (%)
INCEPTION V4 [17]	75	67	75	71
RESNET [17]	82.5	68	82	75
DCNN [17]	73.75	94	93	92
PROPOSED CNN-AUTOENCODER	95.12	96.37	94.65	95.89

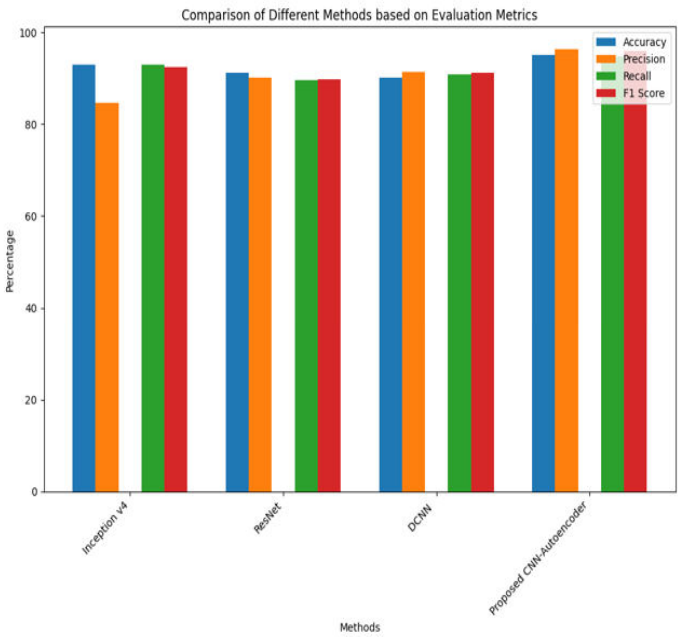

Fig.10. Comparison of Performance Metrics

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G. Discussion

Research advances in the use of models CNN-Autoencoder Hybrid model for medical image analysis This is especially true for diagnosing Alzheimer's disease. It is considered an important progress. This model's ability to achieve an accuracy rate of 95.12%, which is superior to existing models such as Inception v4, ResNet, DCNN [24], highlights the potential of the model. to revolutionize the industry Autoencoding methods may take advantage of the strengths of CNNs, and CNN autoencoders are adept at extracting spatial features from images. Meanwhile, autoencoders are adept at finding effective representations. The combination of these two techniques allows the model to efficiently capture both low-level and high-level features. and improve efficiency The implications of this research are broad. Using the model CNN-Autoencoder The successful completion of a hybrid model for medical image analysis and Alzheimer's disease diagnosis is an important step forward. The model's excellent performance demonstrates the potential of this approach to revolutionize the field and improve patient care.

VI. CONCLUSION AND FUTURE WORK

In this study, the CNN-Autoencoder model was used. It was designed and implemented to evaluate the effectiveness of clinical image analysis in predicting and classifying Alzheimer's disease. The model's performance was evaluated using confusion matrices, accuracy, and loss metrics, demonstrating its ability to differentiate between various stages of dementia: From the confusion matrix it can be observed that there was some misclassification between the classes; however, this misclassification was mostly between adjacent classes, therefore there is room for improvement. Nevertheless, accuracy gained in the experiment was consistently high for both the training and the validation phase finally reaching validation accuracy of around 95.12%. These results were further corroborated by the training and validation loss graphs that showed that the model did not over-fit and thus has good generalization capability. The capability of the model to handle many image computations from the test data whilst still achieving reasonable accuracy indicate viability for real-world clinical use. The future work can include improving the current model to decrease the misclassification rates between different stages of dementia as well as expanding the method to greater and more diverse set of images confirming the effectiveness of the method. This work contributes to providing a bright result to improve AI technologies for the healthcare system with an excellent diagnostic tool to diagnose Alzheimer's disease early.

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