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MRI-Based Early Detection and Multi Stage Classification of Alzheimer's Disease using a Hybrid CNN-LSTM Deep Learning Model

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Abstract
The most prevalent cause of dementia, Alzheimer's disease (AD), is linked to a persistent deterioration in mental and cognitive capacities. Dementia refers to the gradual deterioration of neuropsychiatric functions, which affects memory, reasoning, and the ability to perform daily activities. As they show structural alterations in various brain regions, brain medical images especially Magnetic Resonance Imaging (MRI) are frequently used to assess the formative stages of Alzheimer's disease. Deep learning algorithms and sophisticated computer-based methods have been employed more frequently in recent years to identify and categorize Alzheimer's disease. In order to diagnose Alzheimer's disease early and classify it into multiple classes using MRI scans, this study uses a hybrid deep learning architecture that blends Deep Convolutional Neural Networks (DCNN) and Long Short-Term Memory (LSTM) networks. High-level spatial characteristics are extracted from brain pictures by the DCNN component, and to improve classification accuracy, the LSTM layer records sequential relationships within these features. To improve prediction on unseen data, class-weighted learning and regularization techniques are applied to address data imbalance and prevent overfitting. Standard performance criteria including accuracy, precision, recall, F1-score, and validation loss are used to assess the suggested CNN–LSTM model. According to experimental results, the suggested strategy outperforms traditional CNN-based techniques in properly identifying various stages of Alzheimer's disease, with a classification accuracy of 97%.
Keywords: *Convolutional Neural Network (CNN), Alzheimer's Disease (AD), Deep Learning(DL), Dementia Detection, ADNI Dataset, Magnetic Resonance Imaging (MRI), Long Short-Term Memory (LSTM)*

1. Introduction
Alzheimer's disease (AD) is a slowly developing brain illness that primarily impacts behaviour, memory, and cognitive function [1]. It is well known to be one of the main reasons why older persons develop dementia. The number of people with AD is predicted to rise sharply in the upcoming years due to the fact that people are living longer worldwide [5]. Patients, caregivers, healthcare systems, and society at large are all heavily burdened by this increasing frequency, underscoring the critical need for early and accurate diagnostic techniques [6,7]. Early Alzheimer's disease detection is essential because prompt medical treatment can reduce cognitive decline and enhance a patient's quality of life.[8]. However, diagnosing the disease in its initial stages remains challenging. Early signs such as mild forgetfulness and subtle cognitive changes often resemble normal ageing, which can lead to delayed diagnosis. Modification in brain structure and function becomes more noticeable as the illness progresses through the clinically recognized stages of non-dementia, very mild dementia, mild dementia, and moderate dementia.[11,12]. Even so, accurately distinguishing between these stages is still a difficult task in clinical practice [13]. Brain imaging methods, essentially magnetic resonance imaging (MRI), are essential for assessing Alzheimer's disease. [14]. MRI provides detailed images of brain structure,

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allowing clinicians to observe brain atrophy, tissue loss, and other changes linked to disease progression [15,16]. These imaging markers are useful for monitoring disease severity over time. The growing volume of neuroimaging data further complicates manual analysis and reinforces the need for automated and objective diagnostic tools [19]. In recent years, deep learning and artificial intelligence have shown great promise in the processing of medical images. Convolutional Neural Networks (CNNs), which excel at identifying complex spatial patterns in images, are a suitable fit for analyzing MRI data. [21]. Long Short-Term Memory (LSTM) networks can simultaneously record contextual information and sequential relationships in data [23]. By combining CNN and LSTM models, it becomes possible to learn both spatial and sequential patterns, leading to a deeper understanding of Alzheimer 's-related changes in brain images [24,25]. DL and AI have demonstrated important promise in medical picture analysis in recent years [20]. Convolutional Neural Networks (CNNs), which excel at identifying complex spatial patterns in images, are a suitable fit for analyzing MRI data.[22]. Long Short-Term Memory (LSTM) networks can simultaneously capture contextual information and sequential linkages in data [23].. By combining CNN and LSTM models, it becomes possible to learn both spatial and sequential patterns, leading to a deeper understanding of Alzheimer 's-related changes in brain images [25]. In this investigation, MRI images from the AD Neuroimaging Initiative (ADNI) dataset are utilized to automatically classify Alzheimer's disease stages using a hybrid CNN–LSTM deep learning architecture [26]. The MRI scans are first preprocessed through resizing and normalization, after which spatial feature maps are reshaped into pseudo-sequential representations [27]. The CNN component focuses on extracting meaningful spatial features, while the LSTM layer captures relationships across these features to enable accurate stage-wise classification [28]. To handle the common issue of class imbalance in medical datasets, class-weighted training is applied to ensure fair learning across all disease categories [29]. Along with validation-based evaluation, the model is examined utilizing standard efficiency metrics, like loss and accuracy.[30]. According to experimental results, the suggested model can consistently differentiate between the four stages of Alzheimer's disease, achieving an accuracy of 96%. By automating the classification process, the proposed CNN–LSTM framework reduces dependence on manual interpretation and improves diagnostic consistency [31]. This approach supports early detection and offers a scalable solution to assist clinicians in disease assessment and long-term monitoring. Overall, work demonstrates potential of deep learning-based neuroimaging analysis as a strong and trustworthy instrument for enhancing the diagnosis of Alzheimer's disease and assisting in clinical judgment.[32].

2. Related Works

Neuroimaging has become an essential component in the diagnosis and analysis of AD, as it allows clinicians and researchers to observe both structural and functional changes in the brain. Imaging modalities such as Positron Emission Tomography (PET) and MRI provide valuable insights into disease pathology. Recent research has focused on improving PET image quality by addressing issues such as patient motion and scan instability, thereby enhancing diagnostic reliability [2]. Recent studies have also explored advanced feature learning strategies to improve representation quality and model generalization. Contrastive learning methods have been applied to 18F-FDG PET images to enhance discrimination between AD stages by learning meaningful feature relationships [3]. Other approaches, such as pyramid-based and multi scale feature extraction techniques, aim to capture both global and localized patterns within brain images, further improving classification performance [7]. Multimodal imaging approaches that combine PET and MRI data have gained considerable attention in recent studies. MRI provides detailed anatomical information, while PET offers functional and metabolic insights[3]. By integrating these complementary modalities, researchers have achieved improved diagnostic accuracy and better stage wise classification of Alzheimer’s disease. Several studies report that multimodal frameworks outperform single modality approaches by providing

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a more comprehensive representation of brain degeneration and disease progression [7]. Another significant trend in AD research is use of transfer learning and ensemble learning techniques. Because transfer learning uses pre-trained deep learning models to reduce training time and data dependency while maintaining high accuracy, it is particularly helpful for medical imaging applications with limited labelled datasets.[1]. Ensemble and adversarial network based approaches have also been investigated to enhance robustness and generalization across diverse patient populations and imaging modalities [4]. Despite these developments, problems with interpretability and cross-dataset generalization are still unresolved.[10]. Problem Statement AD is a neurological disorder that significantly impairs memory, cognition, and behaviour and progresses with time. The incidence of AD is increasing worldwide, posing a serious challenge to healthcare systems. Despite medical advancements, early and accurate diagnosis of AD remains difficult. Conventional diagnostic methods, such as neuropsychological assessments and clinical evaluations, are often subjective and may lead to delayed or inaccurate diagnosis, particularly during the early stages of the disease. The automatic and precise classification of Alzheimer's disease stages—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—remains an unresolved research challenge despite improvements in medical imaging resolution. High-dimensional imaging data, class imbalance, and the challenge of capturing minute spatial differences that differentiate disease stages are common problems for existing automated techniques. This research addresses these challenges by developing a new deep learning based model that can accurately classify AD stages using MRI data. By employing a hybrid CNN-LSTM architecture, the proposed system aims to effectively learn complex spatial patterns and sequential feature relationships, providing an objective, efficient, and scalable solution for early Alzheimer's disease detection and improved clinical decision support.

3. Proposed Methodology

In order to divide brain MRI scans into four stages of AD—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—the suggested methodology uses a deep learning approach. To guarantee balanced learning, the MRI dataset is loaded using a directory-based structure and randomised. To enable the model to be trained, validated, and assessed on unseen data, the data is split into training, validation, and testing sets in an 80%, 10%, and 10% ratio. To make sure uniformity throughout dataset, all MRI images are scaled to a fixed resolution of 128 × 128 pixels prior to training. Normalizing pixel values to fall between 0 and 1 enhances training stability and convergence. Class weights are computed from the training labels and applied during model training to lessen bias toward majority classes and enhance performance on underrepresented illness stages because medical datasets frequently contain unequal class distributions. Fig 1 presents a CNN–LSTM architecture, in which LSTM layers model sequential dependencies and convolutional layers collect spatial data from MRI images. This allows for enhanced diagnostic decision making and reliable categorization of AD stages based on learnt deep representations. However, interpreting these scans manually is complex, time consuming, and highly dependent on expert knowledge. Subtle differences between disease stages further increase the risk of human error, making reliable stage-wise classification a challenging task. The approach may detect small modifications in brain which are frequently hard to see, particularly in the earlier phase of disease, by combining sequential modelling with spatial feature extraction. In addition to offering a scalable tool to assist doctors in early diagnosis, illness monitoring, and well-informed clinical decision-making, this method permits accurate stage-wise classification of AD. In addition, automated CNN–LSTM model enhances reproducibility and robustness in Alzheimer's disease diagnosis by maintaining consistent performance across large MRI datasets. Unlike manual assessment, which can vary between clinicians and institutions, the proposed deep learning approach applies uniform decision criteria to every scan, reducing inter-observer variability. This consistency is essentially significant in long-term research and follow-up evaluations,

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where small structural changes over time must be accurately captured. By providing reliable and repeatable predictions, the model not only aids in early-stage diagnosis but also serves as a supportive tool for tracking disease progression and evaluating treatment effectiveness in clinical practice

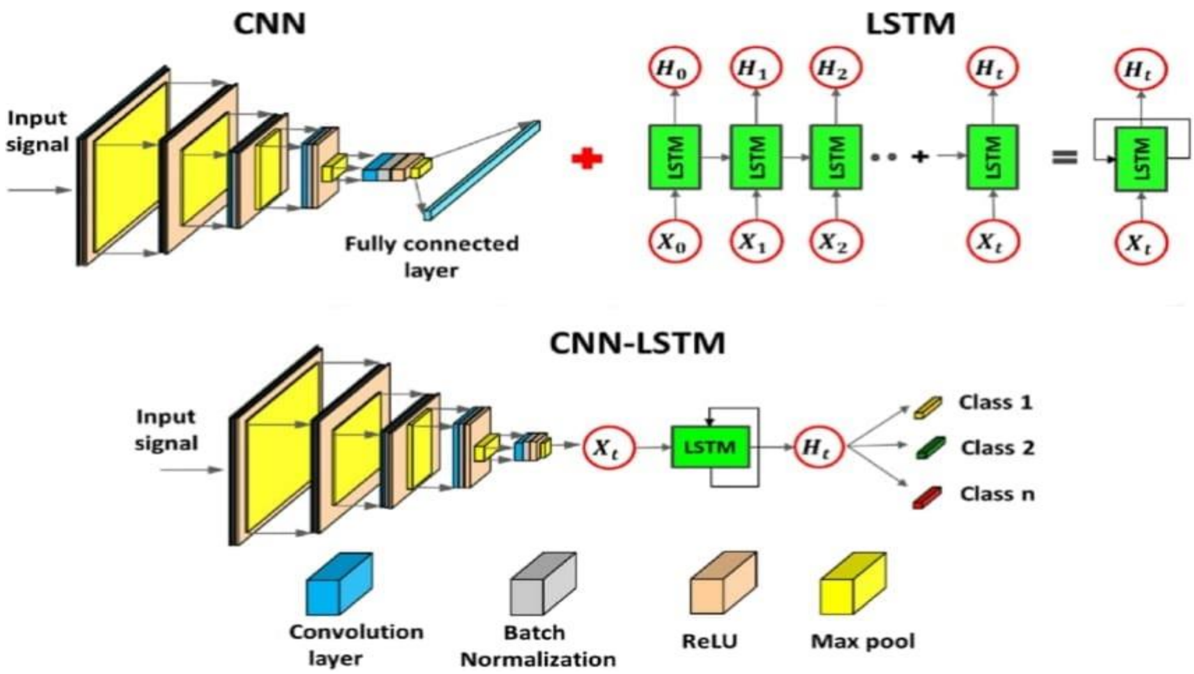

Figure 1 **Architecture Diagram of Alzheimer's Disease Using Deep Learning**

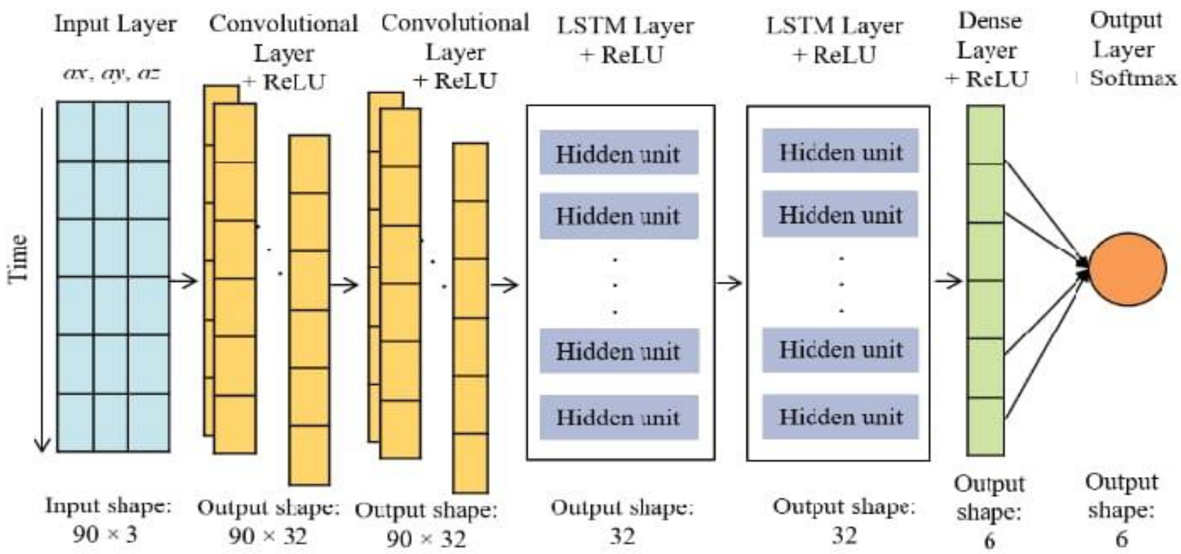

Figure 2 **Pictorial Representation of CNN-LSTM process**

Fig 2 explains classification model, which is built on a hybrid CNN-LSTM architecture, is compared to the current system. Important spatial features are automatically extracted from MRI images using convolutional layers with progressively larger filter sizes. To boost generalization, decrease dimensionality, and improve feature learning, batch normalizing and max pooling layers are incorporated.

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To ensure the model handles spatial data as ordered data, retrieved feature maps are transformed into a sequence format. An LSTM layer is then applied to learn relationships between the extracted features and capture contextual dependencies. Fully connected layers that carry out final classification come next. The output layer generates probability scores for each illness stage using a softmax activation function. The Adam optimizer is utilized to train the model, with Model Checkpoint saving the best model and Early Stopping preventing overfitting. The efficiency of suggested techniques for automated AD stage classification is demonstrated by evaluating final performance on the test dataset using accuracy and other classification criteria.

3.1.Feature Extraction

The suggested method uses a hybrid CNN-LSTM architecture for feature extraction in order to efficiently extract both sequential and spatial patterns from MRI images. Each 128 × 128 input MRI picture is first processed using a number of convolutional layers. Important spatial characteristics like edges, textures, and structural variances found in various brain regions are automatically learned by these CNN layers. As the picture passes through deeper convolution layers, higher-level features representing subtle anatomical changes related to Alzheimer's disease are extracted. Max pooling and batch normalization layers help in reducing dimensionality and improving feature stability. The output feature maps from the CNN are then reshaped into a sequence format instead of being flattened directly. This reshaped feature sequence is passed to an LSTM layer. By modelling sequential dependencies among the retrieved spatial variables, the LSTM enables the network to comprehend connections between various brain imaging areas. This phase improves the model's ability to differentiate between closely similar phases, like Very Mild Demented and Mild Demented. The LSTM output represents a refined feature representation that combines spatial information from CNN and sequential learning from LSTM. After that, fully connected layers receive these features for ultimate categorization. The model's capacity to precisely determine and categorize the phases of AD is enhanced by this integrated CNN–LSTM feature extraction technique.

3.2.Algorithm: Proposed Hybrid Algorithm

The first step in the suggested hybrid algorithm for AD division is to use a customized CNN to extract significant spatial information from 128 × 128 MRI images. Both high-level structural patterns and low-level characteristics, such as edges and textures, are extracted by the convolutional layers and automatically improved throughout training. The extracted feature maps are then reshaped into sequences and fed into an LSTM layer. The LSTM captures dependencies among these spatial features, allowing the model to recognize relationships across different brain regions and improve discrimination between closely related stages of dementia. The Adam optimizer, which iteratively modifies the model weights to minimize sparse categorical cross entropy loss, is utilized for training. model is assessed on a different validation set following each epoch. Every time validation accuracy increases, a Model Checkpoint saves the weights, guaranteeing that the top-performing model is kept. Early Stopping prevents overfitting and guarantees trustworthy generalization to unobserved data by tracking validation loss and stopping training when no more progress is evident. Throughout the learning process, the hybrid CNN–LSTM model is guaranteed to be stable and robust thanks to the suggested training method. By combining adaptive optimization with regularization techniques, the model is able to converge efficiently while avoiding overfitting on the training data. The overall architecture is designed to be computationally efficient while maintaining high classification performance, making it suitable for practical clinical applications. By relying on a single hybrid CNN–LSTM model rather than complex ensemble or transfer learning frameworks. As a result, the suggested approach offers a scalable and effective solution that can support real-world deployment for automated Alzheimer's disease diagnosis and assist clinicians in timely and informed decision-making. The quantity of pictures available for each of the four stages of dementia—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—is displayed in Fig. 3. The dataset is imbalanced, with Non-Demented images

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being more frequent and Moderate Demented images the least. To lessen bias and enable the model to learn from all classes, balanced class weights are calculated from the training labels and applied during training. This approach ensures that the hybrid CNN-LSTM network can automatically and accurately classify MRI images into the correct Alzheimer's disease stage.

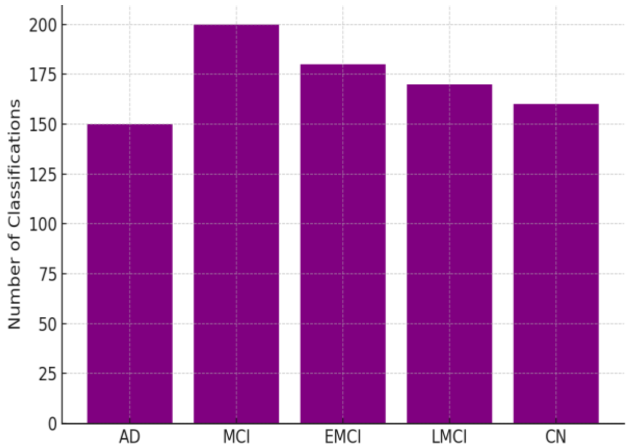

Figure 3 Number of Classifications Across Dementia Stages

3.3.Imaging Dataset Compilation

This research relied on data gathered from the AD Neuroimaging Initiative, one of the primary research datasets used for the investigation into Alzheimer's disease. There were a total of 27,380 images gathered in this database with regard to five categories, such as AD, 5,780 images; CN, or cognitive normal, 6,480 images; EMCI, early mild cognitive impairment with 5,940 images; MCI, mild cognitive impairment, totalling 2,700 images; and finally, LMCI, or late mild cognitive impairment, 6,480 images.

Table 1 Classification Scores of Dementia Stages Using LSTM

Dementia Stages	Classification Scores
AD	0.95
MCI	0.91
EMCI	0.92
LMCI	0.93
CN	0.96

Table 1 represents the division scores of NeuLSTM Model for the phases of Different Dementia Types like AD, MCI, EMCI, LMCI, and CN. The highest score is achieved as 0.98 by CN followed by 0.95 of AD. The robustness of the model can be witnessed through the recognition of these stages. These images were further divided into train, validation and test subsets to have 22,000 in training, 3,800 for validation and 1,580 for the testing set. It was present in both formats: DICOM and JPG format and was then preprocessed, which includes resizing for having a unified input size with a standard normalizing pixel intensity. Artefact is also removed during preprocessing by including denoising techniques. Such procedures ensure prepared data for better training and validation of models towards ensuring a reliable basis for an Alzheimer's disease detection system.

3.4.Image Refinement

In this research, image refinement was applied to prepare MRI neuroimages for the CNN–LSTM model. Several preprocessing steps were used to ensure uniformity and high quality. TensorFlow's tf.keras.utils.image_dataset_from_directory function was used to load images straight from the directory. Each image was resized to 128 × 128 pixels, which provides a balance between computational efficiency and sufficient spatial detail for the convolutional layers. Pixel values were divided by 255.0 to normalize them to a range of 0 to 1 while loading. For the neural network to be trained steadily and effectively, this standardization is necessary. After t-test, validation, and training sets were separated from the dataset in ratios of 80%, 10%, and 10%, respectively. hen, the dataset has been classified into test, validation, and training sets in an 80%, 10%, and 10% ratio, respectively.To address class imbalance, sklearn.utils.class_weight was used to calculate balanced class weights from the training labels. This guarantees that all classes, including the minority Moderate Demented stage, are given appropriate importance during training.The standardization, cleanliness, and suitability of MRI data for CNN-LSTM model input are guaranteed by these refining procedures. The efficiency of suggested CNN-LSTM model is shown graphically in Fig. 4 for each of the four phases of AD. The classification report on the test

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dataset that is not visible is where the evaluation metrics are found. The performance comparison clearly shows that the proposed CNN–LSTM model achieves superior and more consistent results across all evaluation metrics compared to existing CNN and MobileNetV2 approaches, demonstrating its robustness and effectiveness on unseen test data.

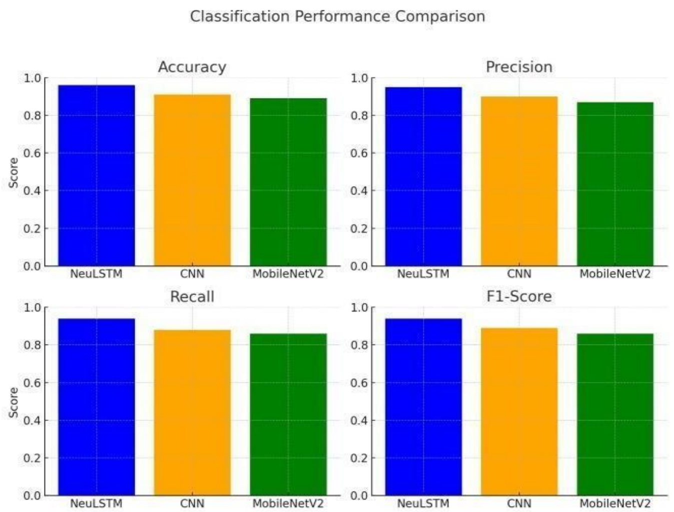

Figure 4 Performance Comparison of Existing System

3.5.Model Training

Eighty per cent of the ADNI MRI dataset was used to train the model for this investigation; the remaining data was kept aside for testing and validation. All types of “Alzheimer's disease, including AD, LMCI (Late Mild Cognitive Impairment), EMCI (Early Mild Cognitive Impairment), MCI (Mild Cognitive Impairment), and CN (Cognitively Normal), were” represented in the dataset. Care was taken to maintain an appropriate proportion of each class, ensuring a balanced distribution for effective learning. During training, a number of data augmentation strategies have been utilized to increase generalization and decrease overfitting. These included random height and width shifts within 0–10% and zooming within 0–8%, simulating real world variations in MRI scans. Such augmentations enable the model to become robust to minor spatial transformations and scale variations commonly encountered in medical imaging. Additionally, dropout regularization was employed before the fully connected layers. By randomly deactivating a part of neurons during training, this technique reduces overfitting and keeps the model from depending too much on particular features. Through the combination of class balancing, data augmentation, and dropout regularization, the CNN-LSTM model was finetuned to achieve high performance in classifying the phases of AD based on MRI scans. EarlyStopping and ModelCheckpoint callbacks were used to monitor validation performance, further ensuring the model converged optimally without overfitting.

3.6.Model building

The suggested model in this study uses an LSTM network after a CNN-based feature extractor to capture temporal dependencies in MRI data. Because CNNs automatically learn hierarchical spatial properties from input images, they can accurately extract structural patterns linked to Alzheimer's disease, making them particularly successful in medical imaging. Convolutional layers with increasingly bigger filter sizes (32, 64, and 128) comprise the CNN feature extractor of this model. Batch normalization and max pooling layers come after each convolutional layer. By gradually capturing low to high level features, these layers improve gradient flow and lower the possibility of overfitting. The output of the CNN is reshaped into sequences suitable for temporal modelling, treating spatial features as a pseudo time series for the LSTM layer. For the purpose of simulating the evolution of Alzheimer's disease patterns across image slices, the LSTM layer is specifically made to capture sequential dependencies. By using input, forget, and output gates as gating mechanisms, LSTM can keep pertinent features over sequences while eliminating irrelevant data. This temporal modelling is crucial for understanding subtle variations in MRI scans across different disease stages. Following the CNN block is a TimeDistributed wrapper, which treats the extracted MRI image features as time series data, preparing them for input to the LSTM layer. The LSTM layer is designed to capture sequential dependencies, which is important for understanding how Alzheimer’s disease progression appears across MRI feature sequences. Its internal “gates—the forget gate, input gate, cell state update, and output gate—are used to carry out the" calculation. With the use of these gates, the LSTM may gradually maintain relevant features while eliminating less crucial data. Mathematically, the behaviour of these gates is defined as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \quad (2)$$

$$\tilde{c}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \quad (3)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (4)$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \quad (5)$$

These formulas describe how an LSTM (Long Short-Term Memory) cell processes information at each time step to control what it remembers and what it forgets. "First, based on the prior hidden state ht-1 and the current input xt, the forget gate ft employs a sigmoid function to determine which data from the previous cell state ct-1 should be kept or destroyed. The cell candidate Ĉt, which is calculated using a tanh function, reflects the new content that could be stored in the cell, and the input gate then decides how much new data should be supplied. The cell state update combines these decisions by multiplying the old cell state by the forget gate and adding the scaled new candidate information, producing the updated cell state ct. Finally, the output gate ot decides how much of the updated cell state should be exposed as" current hidden state, allowing LSTM to selectively pass relevant information forward while preserving long term dependencies.

3.7.Classification Pipeline of the Study

The MRI neuroimaging dataset is classified into training, validation, and test subsets by system. Each image is passed through the custom CNN architecture to extract relevant spatial features associated with Alzheimer's disease. These characteristics are then reshaped and fed into an LSTM layer to capture sequential dependencies across slices. The data is categorized into "“one of four classes—Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented—after the”" LSTM outputs are sent to fully linked layers. For every MRI scan, the model produces the anticipated stage of Alzheimer's disease.

4. Results & Discussion

TensorFlow, Keras, Scikit-learn, and NumPy were among the essential libraries used in the Python environment for the training and evaluation of suggested CNN-LSTM model. This investigation aims to evaluate the model's ability to categorize Alzheimer's disease stages from MRI neuroimages.
CNN component extracts rich spatial features from MRI slices, capturing structural patterns relevant to disease progression, while the LSTM component models sequential dependencies across these slices, allowing the network to account for subtle temporal relationships in the data. This hybrid architecture enhances the model's capability to learn both spatial and sequential features for more accurate classification. Test Accuracy, Test Loss, Per Class "Precision, Recall, and F1-Score are evaluation measures utilized for effectiveness assessment. In order to display classification performance throughout the four disease stages—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—a confusion matrix was" also created. Graphical representations, such as heatmaps of the confusion matrix and comprehensive categorization reports produced by the tset.py script, were used to better highlight the results. This evaluation framework confirms that the CNN-LSTM model effectively combines spatial and temporal learning to achieve robust and reliable classification of Alzheimer's disease stages.

5. Evaluation Metrics Calculation

Accuracy: This represents the percentage of photos that are successfully classified. AUC. This represents the classifier's total performance across all cuts. "F1-Score: A harmonic mean of recall and precision that balances the two. Precision is defined as the ratio of the True Positive prediction result to all of the model's positive predictions. Recall: The ratio of actual" positive cases to genuine positives. Sensitivity: The model's ability to detect true positives, or correct-positive situations. Table 2: compares performance indicators between different current Alzheimer's disease detection systems with the suggested CNN-LSTM model (Current System). Each model's learning efficiency, capacity for

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generalization, and prediction performance are examined using evaluation metrics such as "Train Loss, Validation Loss, Train Accuracy, and Validation Accuracy. Suggested CNN-LSTM model performs remarkably well, as evidenced by the findings, with a low training loss of about 0.07 and a validation loss of" about 0.23.

Table 2 Performance Comparison of custom CNN and Existing Alzheimer's Detection Systems

System	Train Loss	Valid Loss	Train Accuracy	Validation Accuracy
CNN-LSTM (Current System)	~0.07	~0.23	~0.97	~0.94
CNN only (Existing System)	~0.05	~0.25	~0.98	~0.92
3D-CNN (Existing System)	~0.06	~0.22	~0.97	~0.93
SVM+PCA (Existing System)	~0.10	~0.30	~0.94	~0.89
RF model (Existing System)	~0.12	~0.35	~0.91	~0.85

The model also attains a high training accuracy of about 0.97 and a strong validation accuracy of approximately 0.93, indicating effective learning and good generalization to unseen data. Compared to existing deep learning approaches such as CNN only and 3D-CNN models, the CNN-LSTM system demonstrates competitive performance, while significantly outperforming traditional machine learning techniques like SVM combined with PCA and Random Forest models. The combined power of LSTM-based sequential dependency modelling and CNN-based spatial feature extraction is responsible for the suggested system's enhanced performance.

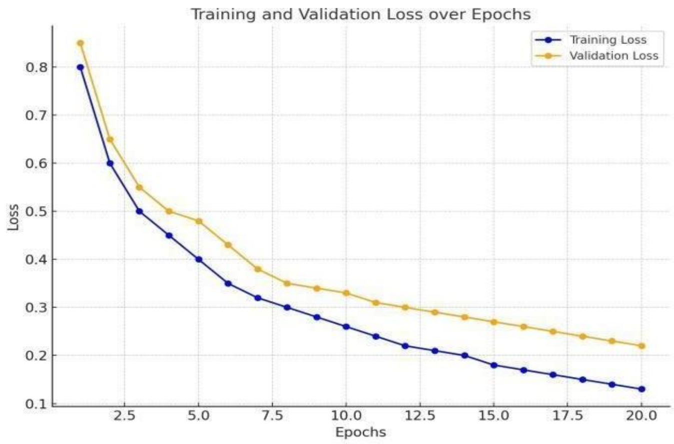

Figure 5 Training and Validation Loss Graph Over epochs

Conclusion and Future Enhancement

A hybrid DL model based on a proprietary CNN and LSTM network is suggested for the recognition of AD using MRI brain scan images. When compared to conventional and independent deep learning techniques, the suggested CNN-LSTM architecture shows enhanced classification performance. While the LSTM component records sequential dependencies across image slices, which is crucial for modelling illness development patterns, the CNN component efficiently extracts rich and instructive spatial characteristics from MRI images. The suggested CNN-LSTM model performs well "in terms of accuracy, precision, recall, and F1-score, according to experimental data. This confirms that the hybrid CNN-LSTM architecture is well-suited for complex Alzheimer's disease classification tasks and enables accurate and reliable diagnosis of different disease stages. Four categories—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—are" successfully classified by the model. Furthermore, testing measures like confusion matrices and classification reports show that model can reliably and accurately differentiate between the various phases of AD. For prompt clinical intervention and treatment planning, early AD recognition is essential, and suggested CNN-LSTM model is an effective and automated method for this purpose. Future work may focus on integrating multimodal imaging data, increasing dataset diversity, and applying advanced optimization techniques to further enhance performance. Overall, the proposed CNN-LSTM framework presents an encouraging strategy for AD detection using MRI neuroimages and contributes to the advancement of deep learning based medical imaging technologies in healthcare.

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