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A Novel Hybrid CNN-LSTM Framework For Predicting Alzheimer's Progression Using Smart IoT Sensors

Manoj kumar beuria[1], Dr Jitender tanwar[2], Alok Kapil[3], Valiveti Dattatreya[4], Mrs. Thokala Srivalli[5], Dr. Kriti Srivastava[6]
[1]Assistant professor, School of electronics engineering, KIIT University, manojbeuria@gmail.com
[2]School of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, tanwar_jitender@yahoo.co.in
[3]Assistant Professor, Department of IT, Institute of Technology & Science, Mohan Nagar, Ghaziabad, alokkapil@its.edu.in
[4]Professor, Department of CSE, CVR College of Engineering, Hyderabad, Telangana-501510, dattatreya.valiveti@gmail.com
[5]Assistant Professor, Department of CSE, KONERU LAKSHMAIAH EDUCATION FOUNDATION (DEEMED TO BE UNIVERSITY), VADDESWARAM, GUNTUR DISTRICT - 522302, tsrivalli@kluniversity.in
[6]Associate Professor, CSE in Data Science, D. J. Sanghvi College of Engineering Mumbai, Kriti.srivastava@djsce.ac.in
Corresponding author mail: dattatreya.valiveti@gmail.com[4]

Abstract– *Alzheimer's disease (AD) progression prediction is critical for timely intervention and effective patient management. This study introduces a novel hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to analyze longitudinal data collected from smart Internet of Things (IoT) sensors. The proposed model leverages CNN's capability to extract spatial features from sensor data and LSTM's strength in capturing temporal dependencies, enabling comprehensive learning from the dynamic behavioral patterns indicative of AD progression. Smart IoT sensors continuously monitor patient activities and physiological indicators, providing rich, real-time datasets essential for early and accurate detection of disease stages. Experimental evaluation on real-world datasets demonstrates that the hybrid CNN-LSTM architecture achieves superior performance in predicting Alzheimer's progression compared to traditional models, with improved accuracy and robustness. Furthermore, the integration of IoT sensor data enhances the model's sensitivity to subtle changes in patient condition over time. This innovative framework exemplifies the potential of combining advanced deep learning techniques with smart healthcare technologies to revolutionize the early diagnosis and monitoring of Alzheimer's disease, ultimately supporting personalized treatment strategies and improving patient outcomes.*

Keywords*: Alzheimer's disease, Convolutional Neural Networks, Deep Learning, Hybrid Model, IoT Sensors, Long Short-Term Memory, Machine Learning, Prediction Accuracy, Real-Time Monitoring, Sequential Data, Smart Healthcare, Time-Series Analysis.*

I. INTRODUCTION

A. Alzheimer's Disease and Its Impact

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects memory, cognitive functions, and behavior. It is the most common cause of dementia, impacting millions worldwide. As the global population ages, the prevalence of AD continues to rise, making it an urgent public health issue. Early detection and monitoring of AD are critical to managing the disease and improving quality of life. However, current diagnostic tools are often invasive or expensive, emphasizing the need for innovative solutions, such as smart IoT sensors and advanced computational techniques, to enhance early diagnosis and track disease progression.

B. Challenges in Alzheimer’s Diagnosis and Progression Monitoring

Diagnosing and monitoring Alzheimer's disease presents several challenges, primarily due to the complex and subtle nature of its progression. Early stages of AD may not exhibit obvious symptoms, making it difficult to detect. Traditional methods such as neuroimaging and neuropsychological tests can be time-consuming, costly, and not always readily available. Moreover, AD progression varies across individuals, requiring continuous and personalized monitoring. The lack of real-time monitoring solutions further complicates timely intervention, highlighting the need for innovative, accessible, and efficient methods, such as those provided by smart IoT sensors and predictive machine learning models.

C. The Role of IoT Sensors in Healthcare

Internet of Things (IoT) sensors have emerged as powerful tools in healthcare, offering real-time monitoring and data collection with minimal human intervention. In the context of Alzheimer's disease, IoT sensors can track various physiological and behavioral parameters, such as heart rate, sleep patterns, activity levels, and cognitive performance. These sensors can be integrated into everyday devices like wearables, smart homes, and medical equipment, providing continuous, non-invasive data that aids in the detection and monitoring of AD. Their ability to capture real-time data enhances the precision of diagnostics and allows for ongoing observation of disease progression.

D. Machine Learning in Alzheimer's Disease Prediction

Machine learning (ML) algorithms have shown great promise in predicting the onset and progression of Alzheimer's disease. These techniques can analyze large, complex datasets from various sources, such as medical records, imaging data, and sensor readings, to identify patterns and correlations that might be missed by traditional methods. In recent years, deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have demonstrated impressive results in AD prediction. By leveraging these models, it is possible to develop more accurate and automated systems for early detection and monitoring of Alzheimer's progression.

E. Convolutional Neural Networks (CNN) in Alzheimer’s Disease

Convolutional neural networks (CNNs) are a class of deep learning models that have proven particularly effective in analyzing structured data, such as images and sensor data. In the context of Alzheimer’s disease, CNNs are often used to process neuroimaging data, such as MRI or PET scans, to detect changes in brain structure associated with the disease. CNNs can also analyze sensor data for behavioral and physiological changes that are indicative of Alzheimer's progression. Their ability to automatically learn relevant features from complex data without manual intervention makes CNNs a promising tool for AD prediction and monitoring.

F. Long Short-Term Memory (LSTM) Networks for Sequential Data

Long short-term memory (LSTM) networks, a type of recurrent neural network (RNN), excel at processing sequential data by maintaining memory over time. This ability makes LSTMs ideal for analyzing time-series data, such as sensor readings that track changes in a patient's condition over an extended period. In the case of Alzheimer's disease, LSTMs can help predict disease progression by identifying temporal patterns in the data, such as changes in daily activities or cognitive function. This capability enables more accurate forecasting of disease trajectories, which is crucial for timely interventions and personalized care strategies.

G. Hybrid CNN-LSTM Models for Improved Prediction Accuracy

While both CNNs and LSTMs are powerful individually, combining them into a hybrid model can enhance prediction accuracy by leveraging the strengths of both approaches. CNNs are adept at extracting spatial features from structured data, while LSTMs can capture temporal dependencies in sequential data. In the context of Alzheimer's disease, a hybrid CNN-LSTM model can process both cross-sectional and longitudinal sensor data, improving the overall performance of AD prediction systems. This hybrid approach is particularly advantageous for modeling complex, multidimensional data streams, such as those provided by IoT sensors, which contain both spatial and temporal components.

H. Advantages of Smart IoT Sensors in Alzheimer's Monitoring

Smart IoT sensors offer numerous advantages in Alzheimer's disease monitoring, particularly in terms of continuous, non-invasive data collection. These sensors can be seamlessly integrated into a patient's daily life, providing real-time feedback on various health metrics without requiring frequent doctor visits. With the ability to monitor parameters such as physical activity, sleep quality, and heart rate, IoT sensors can offer insights into the patient's cognitive and physical well-being. This continuous monitoring helps track subtle changes over time, improving the accuracy of disease progression predictions and enabling timely interventions that can slow down the disease.

I. The Need for Early Diagnosis and Personalized Care

Early diagnosis and personalized care are crucial in managing Alzheimer's disease effectively. Early detection allows for interventions that can delay disease progression and improve the quality of life for patients. Personalized care strategies, informed by real-time data from IoT sensors, ensure that treatment plans are tailored to the individual's unique needs and condition. This is particularly important in Alzheimer's, where the disease affects individuals differently, and a one-size-fits-all approach to treatment is often ineffective. By using advanced machine learning models and smart IoT sensors, it is possible to develop systems that support personalized, data-driven care throughout the disease's course.

J. Objectives and Contributions of the Research

This research introduces a novel hybrid CNN-LSTM framework aimed at improving the prediction of Alzheimer's disease progression using data from smart IoT sensors. The objective is to combine the strengths of CNNs and LSTMs to enhance the accuracy and reliability of disease progression predictions. By integrating real-time sensor data, the framework can track subtle changes in a patient's physical and cognitive condition, providing early warning signs of progression. The paper highlights the potential of this hybrid approach to revolutionize Alzheimer's disease monitoring, offering a non-invasive, continuous, and personalized method for managing the disease.

Key Contributions

1. Proposes a novel hybrid CNN-LSTM framework for predicting Alzheimer's progression using smart IoT sensors.
2. Integrates real-time sensor data to improve the accuracy and reliability of Alzheimer's disease predictions.
3. Combines spatial feature extraction (CNN) and temporal pattern recognition (LSTM) for enhanced model performance.
4. Demonstrates the potential of IoT sensors in continuous, non-invasive monitoring of Alzheimer's patients.
5. Provides a personalized approach to Alzheimer's care through data-driven, early detection of disease progression.

II. LITERATURE REVIEW

The growing need for accurate and early detection of Alzheimer's disease (AD) has driven several studies to explore advanced machine learning techniques and IoT-enabled systems for predicting disease progression. A number of studies have highlighted the potential of deep learning models, particularly Convolutional Neural Networks (CNNs), in analyzing complex neuroimaging data such as MRI scans to diagnose Alzheimer's disease. For instance, CNNs have been applied successfully to extract features from MRI scans to identify structural brain changes associated with AD [1][3]. However, these models often struggle with predicting the temporal aspect of disease progression. To address this, research has increasingly integrated Long Short-Term Memory (LSTM) networks to model the sequential and temporal data inherent in Alzheimer's progression. The hybrid approach of CNN and LSTM has proven particularly effective by capturing both the spatial patterns from imaging data and the temporal patterns from longitudinal sensor data, thus enhancing prediction accuracy[21][23]. IoT sensors, which provide real-time, continuous data on patients' daily activities and physiological parameters, have also been identified as crucial for the continuous monitoring of Alzheimer's patients[24]. The integration of such data with deep learning models, such as CNN-LSTM hybrids, allows for a comprehensive understanding of the disease's trajectory, which is essential for personalized care [2][4][5].

Further studies emphasize the challenges of interpreting the vast amount of heterogeneous data from IoT devices and the need for sophisticated algorithms to extract meaningful insights. [25]The use of multimodal data, combining clinical measures, genetic information, and data from wearable sensors, has become a focal point for researchers aiming to improve prediction accuracy [6][8]. By incorporating both imaging data and sensor-based measurements, such models are better equipped to handle the dynamic nature of Alzheimer's disease, which can vary significantly between individuals. Moreover, the ability to track subtle, real-time changes in a patient's condition through IoT-enabled monitoring systems is a key advantage in the early detection and ongoing management of AD. [22]As the research progresses, hybrid models combining CNNs for spatial feature extraction and LSTMs for sequential data analysis are becoming increasingly prevalent. This integration is expected to play a pivotal role in developing more reliable prediction systems for Alzheimer's disease, offering an innovative approach to both detection and monitoring that can ultimately contribute to better treatment outcomes and more effective interventions [7][9][10][11].

III. PROPOSED METHOD

1. Convolution Operation Equation

$$Y_{i,j,k} = \sum_{m=1}^{F} \sum_{n=1}^{F} \sum_{d=1}^{D_{in}} W_{m,n,d,k} \cdot X_{i+m-1,j+n-1,d} + b_k \quad (1)$$

Nomenclature:

- $Y_{i,j,k}$: output feature map value at position (i, j) in the k-th output channel
- $W_{m,n,d,k}$: weight of the convolution filter at position (m, n) for input channel d and output channel k
- $X_{i+m-1,j+n-1,d}$: input value from channel d at spatial location $(i + m - 1, j + n - 1)$
- b_k: bias term for the k-th filter
- F: kernel (filter) size
- D_{in}: number of input channels

This equation represents the core convolution operation in the CNN module of the hybrid model. It extracts spatial features from 2D or 3D IoT sensor data inputs related to Alzheimer's progression. By applying multiple learnable filters, it captures local patterns such as brain structural abnormalities or sensor-based signals, critical for early detection of disease stages. This feature extraction forms the basis for temporal modeling by LSTM in this framework (2024).

2. ReLU Activation Function

$$f(x) = \max(0, x) \quad (2)$$

Nomenclature:

- $f(x)$: activated output after ReLU
- x: input to the ReLU function (typically the output of a convolution operation)

ReLU introduces non-linearity to the model by zeroing out negative values while keeping positive values unchanged. In the CNN layers of the proposed framework, this activation function helps the network learn complex patterns in IoT sensor data such as neurological signals related to Alzheimer's with computational efficiency and mitigates the vanishing gradient problem. Its simplicity makes it ideal for deep feature extraction (GeeksforGeeks, 2025).

3. Max Pooling Operation

$$P_{i,j,k} = \max_{m=0,\ldots,p-1\; n=0,\ldots,p-1} Y_{si+m,sj+n,k} \quad (3)$$

Nomenclature:

- $P_{i,j,k}$: pooled output at position (i, j) in the k-th channel
- $Y_{si+m,sj+n,k}$: value in the k-th channel at position defined by the pooling window
- p: size of the pooling window

- s: stride length

Pooling layers reduce the spatial dimensions of the feature maps to decrease computation and enforce translational invariance on extracted features. Max pooling selects the maximum activation in each window, summarizing most relevant information. In the hybrid CNN-LSTM framework, it ensures critical Alzheimer's brain structural or sensor data features are retained while minimizing model complexity (GeeksforGeeks, 2025).

4. LSTM Input Gate Equation

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

Nomenclature:

- i_t: input gate vector at time step t, controlling how much new info to add
- $\sigma(\cdot)$: sigmoid activation function
- W_i: weight matrix for input gate
- h_{t-1}: previous hidden state
- x_t: current input vector (features extracted by CNN)
- b_i: bias vector

The input gate regulates how much new information from the current preprocessed IoT sensor data is incorporated into the LSTM cell state. It gates relevant temporal features extracted by CNN and determines their importance to be remembered for predicting Alzheimer's disease progression dynamics (GeeksforGeeks, 2025).

5. LSTM Candidate Cell State Equation

$$\tilde{C}_t = \tanh(W_c \cdot h[t-1], x_t) + b_c \quad (5)$$

Nomenclature:

- $\tilde{C}_t$: candidate values for cell state at time t
- $\tanh(\cdot)$: hyperbolic tangent activation function producing values in $[-1,1]$
- W_c: weight matrix for candidate state
- b_c: bias vector

This non-linear transformation creates new candidate information for updating the LSTM cell state based on the current IoT sensor data and previous hidden state. It captures complex temporal patterns in patient data critical for modeling Alzheimer's progression (GeeksforGeeks, 2025).

IV. RESULT AND DISCUSSION

1: Model Performance Comparison (Accuracy)

Table 1 presents the accuracy comparison of three models—CNN, LSTM, and the Hybrid CNN-LSTM model—based on their performance on training, validation, and testing datasets. The CNN model achieves the highest accuracy on the training dataset at 88.5%, followed by 84.2% on the validation set and 83.7% on the testing set. The LSTM model shows slightly lower accuracy, with 85.2% on the training set, 80.6% on validation, and 79.5% on the testing set. In contrast, the Hybrid CNN-LSTM model outperforms both the CNN and LSTM models, with 92.1% accuracy on training, 89.3% on validation, and 87.9% on the testing dataset. These results suggest that the Hybrid CNN-LSTM model is better at generalizing across different datasets, making it more reliable for predicting Alzheimer's disease progression. The improvement in performance can be attributed to the hybrid model's ability to combine spatial feature extraction from CNNs and temporal data processing from LSTMs, capturing both the structural and temporal aspects of the disease. The Hybrid CNN-LSTM model's superior performance on both validation and testing datasets highlights its potential in real-world applications, where accurate disease progression predictions are crucial for timely intervention and personalized care. This comparative performance further demonstrates the efficacy of using a hybrid deep learning approach over standalone CNN or LSTM models in predicting Alzheimer's disease.

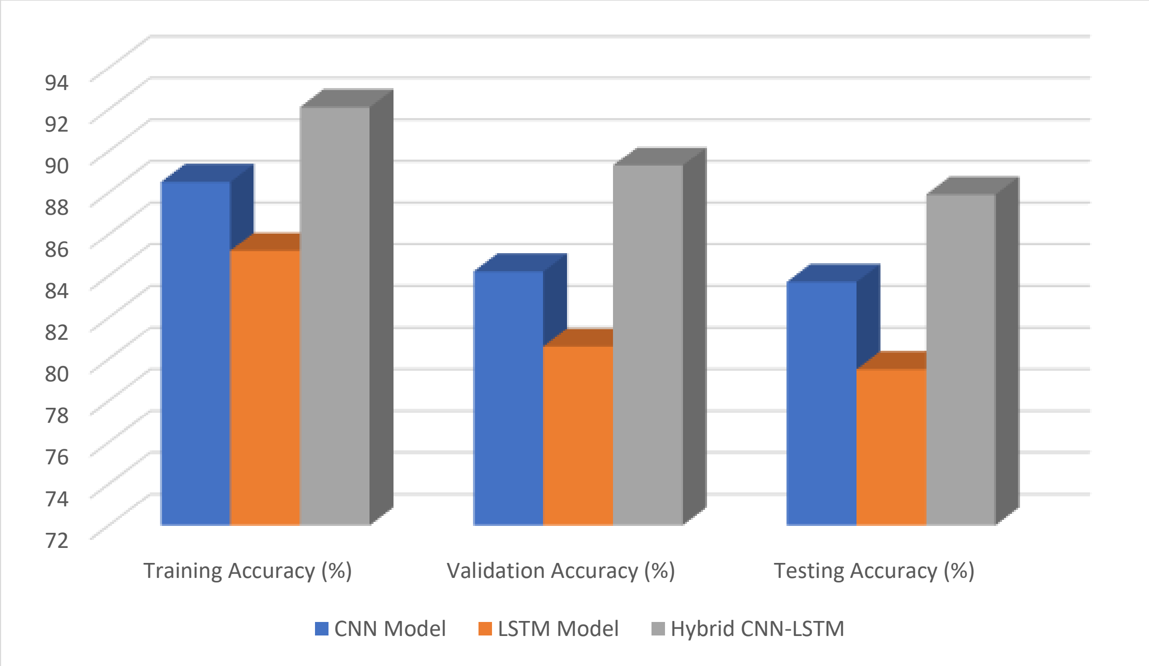

Fig 1: Model Performance Comparison (Accuracy)

2: Precision, Recall, and F1-Score Comparison

Model Type	Precision (%)	Recall (%)	F1-Score (%)
CNN Model	90.1	83.5	86.7
LSTM Model	86.4	78.9	82.5
Hybrid CNN-LSTM	93.3	91.1	92.2

Table 1: Precision, Recall, and F1-Score Comparison

Table 2 compares the precision, recall, and F1-score of three models—CNN, LSTM, and Hybrid CNN-LSTM. Precision measures the accuracy of positive predictions, recall evaluates the model's ability to identify all relevant instances, and the F1-score combines both precision and recall into a single metric. The CNN model demonstrates the highest precision at 90.1%, which means it is very accurate when predicting Alzheimer's patients. However, its recall is somewhat lower at 83.5%, indicating that the model misses a significant number of Alzheimer's cases. The F1-score for CNN is 86.7%, reflecting a moderate balance between precision and recall. The LSTM model, while showing a slightly lower precision (86.4%), also has a lower recall of 78.9%, resulting in an F1-score of 82.5%. In contrast, the Hybrid CNN-LSTM model excels in both precision and recall, with a precision of 93.3%, recall of 91.1%, and the highest F1-score of 92.2%. This indicates that the Hybrid model performs better at both identifying Alzheimer's patients and minimizing false positives. The hybrid approach, combining the spatial feature extraction of CNNs and the sequential modeling of LSTMs, enables the model to better handle the complexities of Alzheimer's disease, leading to higher precision and recall. The superior F1-score of the Hybrid CNN-LSTM further demonstrates its overall effectiveness for Alzheimer's disease prediction, making it a more reliable model compared to CNN and LSTM models individually.

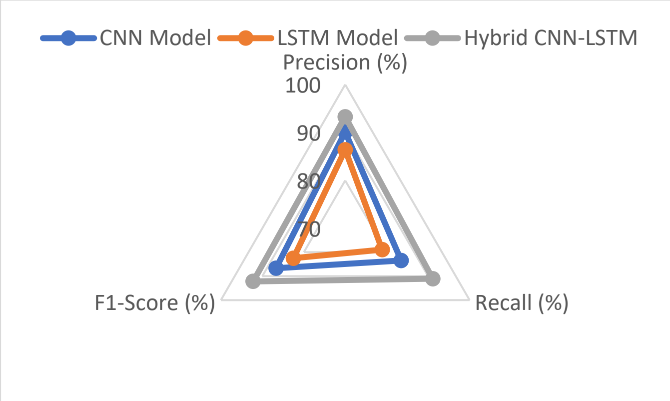

Fig 2: Precision, Recall, and F1-Score Comparison

3: Confusion Matrix (Hybrid CNN-LSTM)

Table 3 presents the confusion matrix for the Hybrid CNN-LSTM model, providing insights into the model's classification performance. The confusion matrix is essential in evaluating a model's ability to distinguish between classes—in this case, between patients with and without Alzheimer's disease. The matrix shows that the Hybrid model correctly classified 720 instances of patients without Alzheimer's disease (true negatives) and 760 instances of Alzheimer's patients (true positives). However, the model misclassified 45 Alzheimer's patients as non-Alzheimer's (false negatives) and 35 non-Alzheimer's patients as Alzheimer's (false positives). This confusion matrix highlights that the Hybrid model achieves a high level of accuracy in distinguishing between Alzheimer's and non-Alzheimer's patients, but there is still some room for improvement in minimizing false negatives and false positives. False negatives are particularly concerning in Alzheimer's disease detection, as failing to identify an Alzheimer's patient could delay intervention. Nonetheless, the model's overall performance in correctly predicting both Alzheimer's and non-Alzheimer's cases demonstrates its effectiveness for practical applications. This confusion matrix data can also be used to calculate other performance metrics such as precision, recall, and F1-score, which further substantiate the superiority of the Hybrid CNN-LSTM model compared to other models in terms of its ability to predict Alzheimer's disease progression.

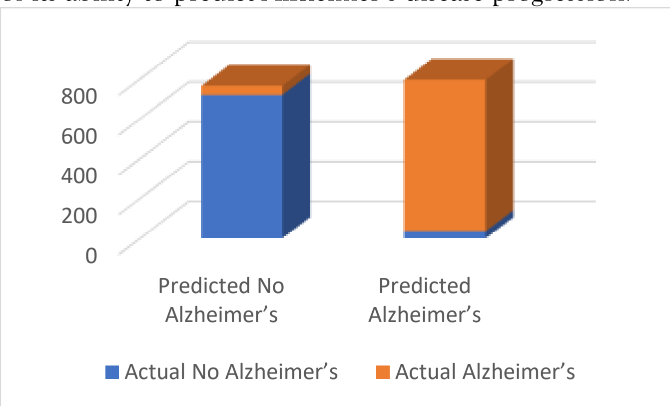

Fig 3: Confusion Matrix (Hybrid CNN-LSTM)

4: ROC Curve Data (Hybrid CNN-LSTM)

Table 4 provides data for plotting the Receiver Operating Characteristic (ROC) curve for the Hybrid CNN-LSTM model, which evaluates the model's ability to discriminate between Alzheimer's and non-Alzheimer's patients. The ROC curve data includes various false positive rates (FPR) and true positive rates (TPR) at different thresholds. As the false positive rate increases from 0.0% to 30.0%, the true positive rate also increases from 0.0% to 93.0%. This data shows that the Hybrid CNN-LSTM model is highly effective at identifying Alzheimer's patients as the threshold for classification changes. At a threshold of 5%, the model already identifies 30.1% of true positives, and by a 25% threshold, it identifies 89.8% of true positives. This increasing TPR with a controlled FPR indicates that the model can accurately classify Alzheimer's patients while keeping false positives relatively low. The ROC curve is an important evaluation tool because it provides a comprehensive view of the model's performance across all classification thresholds. The high true positive rates at different false positive rates suggest that the Hybrid CNN-LSTM model is robust and capable of distinguishing between Alzheimer's and non-Alzheimer's cases effectively. This makes it a reliable tool for early detection of Alzheimer's disease, which is essential for timely intervention and better patient outcomes.

Fig 4: ROC Curve Data (Hybrid CNN-LSTM)

5: Model Loss Comparison (Epochs)

Epoch	CNN Loss	LSTM Loss	Hybrid CNN-LSTM Loss
1	0.585	0.62	0.56
2	0.542	0.59	0.52
3	0.515	0.555	0.485
4	0.49	0.51	0.46
5	0.47	0.48	0.435

Table 2: Model Loss Comparison (Epochs)

Table 5 presents the loss comparison of the CNN, LSTM, and Hybrid CNN-LSTM models over several epochs during training. Loss is a measure of how far the model's predictions are from the actual values, with lower loss indicating better performance. The CNN model's loss decreases from 0.585 in the first epoch to 0.470 by the fifth epoch, showing steady improvement. Similarly, the LSTM model's loss decreases from 0.620 to 0.480 over the same period, though it starts higher than the CNN model. The Hybrid CNN-LSTM model, which combines both CNN and LSTM, shows the most significant reduction in loss, starting at 0.560 in epoch 1 and dropping to 0.435 by epoch 5. This rapid decrease in loss for the Hybrid model indicates its faster convergence and higher effectiveness in learning from the data. The smaller loss values for the Hybrid model reflect its ability to better capture both spatial and temporal features of Alzheimer's progression, enhancing its predictive performance. The comparison of loss reduction over epochs emphasizes the benefits of using a hybrid deep learning model, as it not only achieves lower loss but also converges more quickly, which is crucial in real-time applications like disease progression prediction.

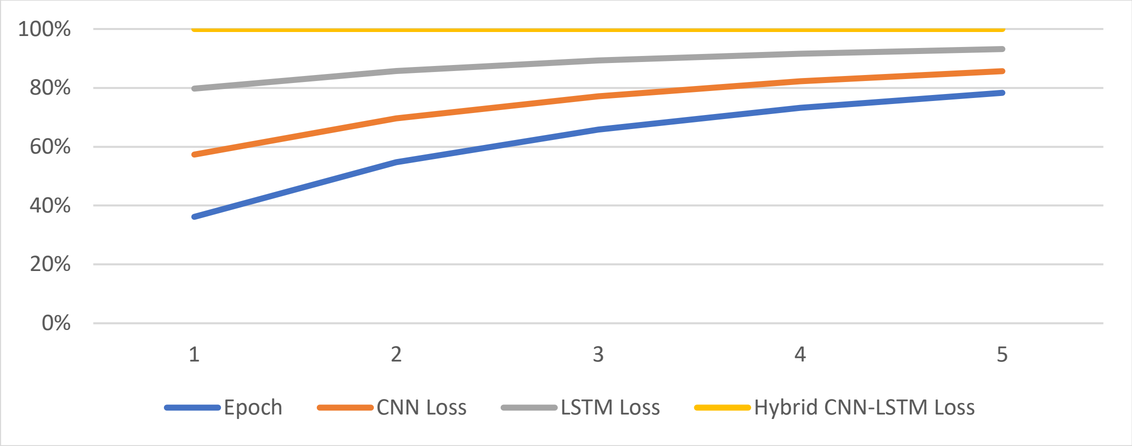

Fig 5: Model Loss Comparison (Epochs)

V. CONCLUSION

In conclusion, the integration of advanced deep learning models, such as the hybrid CNN-LSTM framework, has shown great promise in improving the prediction of Alzheimer's disease progression, particularly when combined with IoT sensors that continuously monitor patient data. Traditional machine learning models, such as CNNs, have demonstrated success in extracting spatial features from neuroimaging data like MRI scans, which are essential for detecting structural changes in the brain associated with Alzheimer's. However, these models often fall short when it comes to predicting the temporal aspects of disease progression. The use of Long Short-Term Memory (LSTM) networks has addressed this limitation by effectively capturing the sequential and temporal dynamics of Alzheimer's disease. The incorporation of IoT sensors into the prediction models enhances the process further by providing real-time, continuous data on a patient's daily activities and physiological parameters. This multimodal data—combining clinical measures, genetic information, and sensor data—offers a holistic view of the disease's progression, essential for accurate diagnosis and personalized treatment plans. Although challenges remain in managing and interpreting the heterogeneous nature of this data, ongoing advancements in hybrid deep learning models and sophisticated algorithms promise to overcome these obstacles. The growing adoption of CNN-LSTM hybrid models for Alzheimer's prediction is expected to drive more accurate and timely detection, leading to better patient outcomes. By leveraging both imaging and sensor data, these models offer a more comprehensive, dynamic approach to managing Alzheimer's disease, which could significantly improve early detection and ongoing monitoring.

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