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Hybrid IOT Based Model for Improving E-Healthcare System

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Abstract- This study evaluates an IoT-enabled healthcare system for predicting diabetes patient outcomes using LSTM network. The proposed LSTM-based model outperforms traditional methods in key metrics such as accuracy, precision, recall, and F1-score. The study uses a dataset of 768 records of Pima Indian female patients aged 21 and above, with nine features: pregnancies, glucose level, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function, age, and outcome. The LSTM network is designed to address the temporal dependencies and complex relationships inherent in the dataset. The study compares the performance of the LSTM-based system with traditional models through the construction of confusion matrices. These matrices are used to compute and analyze F1 scores, recall values, precision, and overall accuracy of the models. The proposed system exhibits significantly improved performance across all metrics, underscoring its efficacy in accurately predicting diabetes outcomes. The accuracy achieved by the LSTM model surpasses that of traditional models, while the error rate is notably lower, emphasizing its reliability and robustness. A comparative analysis with prior research highlights the advantages and potential limitations of the proposed LSTM-based IoT healthcare system. While it excels in handling sequential and time-dependent data, it requires a substantial amount of computational resources and training time. Despite these limitations, the improved prediction outcomes justify its implementation in real-world IoT healthcare systems, where accuracy and reliability are paramount.

Keywords- IoT, Deep Learning, LSTM, Healthcare, Accuracy.

I.INTRODUCTION

IoT refers to devices with sensors communicating over the internet or LAN, enabling healthcare research. LSTM-based AI methods can improve medical prescription and diagnosis accuracy. IoT systems bridge the gap between digital and physical realms, improving user experiences, decision-making, and streamlining operations. Common wireless and wired protocols include Wi-Fi, Bluetooth, Zigbee, and cellular networks. IoT systems are comprehensive product or service automation and analytics platforms that include AI, sensors, networking, and cloud messaging. Secure wireless networks allow IoT devices to connect with IoT platforms. Health care systems are networks of medical facilities treating defined populations, with factors such as funding, workforce, data, and clean facilities essential for smooth operation. WHO recognized the 1980 global eradication of smallpox as the first disease eradicated from the human population due to intentional health care efforts. Health Information Technology (Health IT) is a digital technology that improves patient care, streamlines operations, and enhances healthcare system efficiency. It includes telemedicine, mobile health apps,

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health information exchanges, and electronic health records (EHRs). EHRs store, retrieve, and share patient data, enabling better care coordination and reducing medical errors. Telemedicine improves access to treatment in underserved areas, while health information exchanges ensure data accessibility across different settings. Despite challenges like data privacy, security, and interoperability, Health IT has the potential to transform the industry by making healthcare more efficient, data-driven, and patient-centered. It also encourages patient participation in their care through patient portals. IoT can help healthcare professionals better understand patients' medical conditions, track their activities, and enable real-time monitoring. IoT has the potential to revolutionize healthcare by improving patient care, hospital administration, and medical research. It allows real-time monitoring of patients, reducing hospital visits and improving quality of life. Telemedicine also benefits from IoT, allowing remote diagnosis and treatment in rural or impoverished areas. IoT-enabled devices and platforms improve operational efficiency, streamlining clinical procedures, and enhancing patient care. Telemedicine expands access to healthcare services and improves patient convenience. IoT also supports asset and inventory management in healthcare facilities, enabling real-time visibility. IoT-enabled medication management solutions improve treatment outcomes and patient safety. LSTM artificial neural networks are superior to traditional RNNs in handling discrete data points. In summary, this research makes significant contributions across multiple dimensions: it analyzes the current state of IoT in healthcare, proposes a novel LSTM-based mechanism, enhances performance metrics, and conducts a comprehensive comparative analysis. These contributions collectively advance the understanding and capabilities of IoT-based medical prediction systems, ultimately leading to better healthcare solutions and improved patient care.

- **Analysis of existing IoT-based studies:** This research contributes significantly by conducting a thorough analysis of existing IoT studies, particularly within the healthcare sector. By investigating factors that influence performance and accuracy, this work identifies key gaps and challenges in current IoT medical systems. By offering benchmarks and stressing effective strategies, the findings will let academics and professionals working on IoT healthcare applications enhance them. This complete awareness of the present study helps one to make further development in medical prediction systems.
- **Proposing LSTM-based intelligent approach:** The article proposes a unique approach combining LSTM networks with IoT technologies to enhance medical prediction and prescribing. Using the features of LSTM in processing sequential data, proposed aims to significantly improve accuracy of medical predictions. Significantly, this study offers a modern approach that guarantees accurate and timely medical forecasts by overcoming the limits of traditional prediction methods. LSTM networks have helped IoT devices to assess complex medical data much more effectively.
- **Enhancing performance metrics:** This work also seeks to improve performance of proposed by means of exhaustive assessments of it utilizing significant criteria. Main objective of project is to systematically improve these performance criteria and thereby build a dependable medical prediction system that constantly generates great results. Thanks to the concentration on performance enhancement, the produced model is theoretically strong and practically successful. It will improve patient outcomes and significantly help medical prognosis.
- **Comparative analysis with existing techniques:** An important addition of this work is the analysis of proposed LSTM-based with present techniques in medical prediction. This study clarifies the advantages and efficiency of combining LSTM with IoT systems by meticulously evaluating the strengths and weaknesses of the proposed technique relative to current approaches. By means of a comparative research, the proposed model is shown to be more accurate and efficient as well as to exhibit higher performance. Through identification of issue areas and a benchmark against which to assess them, this study prepares the path for further developments in medical prediction systems.

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II. LITERATURE REVIEW

This investigates integration of LSTM networks within IoT-based healthcare systems to enhance medical prediction accuracy. The study identifies limitations in existing IoT frameworks and proposes an LSTM-based model to address these shortcomings. Through a comparative analysis, the chapter demonstrates the superior performance of proposed model of accuracy paramters. These findings establish LSTM-integrated IoT as robust solution for improving medical prediction outcomes. There have been several researches in area data mining, healthcare and neural network.

Table 1 Related Work for Role of IoT in Healthcare

Author / Year	Objective	Methodology	Limitation
Albahri, A. S., et al. (2021)	IoT-based telemedicine for	Review of state-of-the-art IoT telemedicine systems	General overview, lacks implementation specifics
Durga, S., (2019)	Survey on machine learning and DL	Comprehensive literature review	Rapidly evolving field, some newer methods not covered
Badran, D., (2019)	Blood pressure measurement	Review and comparison of various methods	Focuses on technology, limited clinical validation
Selvaraj, N. (2018)	Feasibility of noninvasive blood pressure measurement	Experimental validation using chest-worn patch sensor	Limited sample size, accuracy compared to traditional methods
Baker, S. B., (2017)	Technologies, challenges, and opportunities in IoT for smart healthcare	Review of existing IoT technologies in healthcare	General overview, lacks specific implementation details
T. C. Arcadius / 2017	Examining the IoT, IoE, and IoNT Protocols	Internet of Things	There is a pressing demand for security-related employment.
J. H. Abawajy / 2017	IoT Obstacles and Current Research on Data Mining for Healthcare	Internet of Things	To talk about architecture is not enough; all aspects must be taken into account.
Hasan, M. K., et al. (2024)	Key agreement and authentication protocol for IoT	Survey of key agreement and authentication methods	Focused on security protocols, lacks practical implementation examples
Zeng, F., (2024)	Sensors in IoT for smart cities	Systematic literature review	Limited to sensor technologies, other aspects not covered
Soori, M., (2023)	IoT for smart factories in Industry 4.0	Review of IoT applications in Industry 4.0	General overview, lacks specific case studies
Singh, D. (2023)	Internet of Things	Technological advancements in manufacturing	Focused on manufacturing, other industries not covered
Portilla, L., et al. (2023)	Wirelessly powered large-area electronics for IoT	Development and testing of wirelessly powered electronics	Limited to specific technology, scalability issues
E. P. Yadav / 2018	An Intelligent Method for Boosting Blood Donation Efficiency	Internet Of Things	Performance has to be improved.
K. Lam / 2016	IoT Overview: Privacy and Security	IoT	A critical component is missing: actual implementation.
Chirag M. Shah / 2014	(IoT)-based Intelligent Security Solutions	Internet of Things	The security of the system must be improved.
Dutta et al. (2020)	Verified COVID-19 case predictions using CNN-LSTM	Combined CNN and LSTM for forecasting	Data quality issues and potential overfitting
Xiong, J., et al. (2018)	Enhancing privacy for data clustering in IoT	Development of a secure data clustering method	Focuses primarily on electrical service, may not generalize to all IoT applications
Muhammad / 2017	An IoT Message Forwarding Model Based on K-Means Clustering	Big Data	Performance has to be improved.
P. Gope / 2016	A Modern Healthcare Built on Secure IoT: BSN-Care Development of WSN-Based Healthcare from Micro to Nano	Internet of Things	There has only been a little amount of progress in research.
K. Srinivas / 2010	Health Data Mining and Heart Attack Prediction Applications	Data Mining	A lot of improvement is needed.
Awad, A. I., et al. (2024)	AI-powered biometrics for IoT security	Review and future vision	Lacks practical implementation examples
Ghaffari, A., et al. (2024)	Securing IoT using machine and deep learning methods	Survey of security methods	Focused on security, other IoT aspects not addressed
Nofrialdi, R., (2023)	Impact of IoT on work effectiveness, individual behavior, and supply chain	Analysis of IoT impacts	Limited to specific case studies, broader applicability not tested
Tun, S. Y. Y., (2021)	IoT applications for elderly care	Reflective review	Limited by rapidly changing technology

Han, C., et al. (2019)	Function chain mapping in IoT networks	Service function chain mapping mechanism	Scalability issues for larger networks
Mahdi H. Miraz / 2017	Healthcare Big Data Analytics: A Comprehensive Review	Internet of Things	It's important to keep the impacting element in mind.
S. Sarkar / 2016	A Model for Mobile Cloud Computing	Cloud Computing	Lack of understanding on how to execute it.
L. A. Tawalbeh / 2016	Identity in the IoT: Emerging Possibilities and Difficulties	Cloud Computing	Inability to reduce the amount of space and time used
A. R. Biswas / 2014	Internet of Things and Cloud Convergence: Possibilities and Difficulties	Internet of Things	During implementation, there is a lack of performance.
Saranya, T., et al. (2023)	Deep learning and IoT	Comparative analysis	Limited to agriculture, may not generalize to other sectors
Farnham, T. (2019)	Indoor localisation of IoT devices	Radio environment mapping for indoor localisation	High computational complexity, limited to specific environments
Arun Pushpan / 2017	IoT: Problems and Difficulties from an Indian Point of View	Data Mining	There is a paucity of expertise in the field.

Research gap

The IoT has been used in healthcare systems to enhance medical prediction and security. Comprehensive study of IoT applications in industry considers data quality, sensor dependability, and the convergence of IoT with cloud computing. An intelligent strategy integrating LSTM networks into IoT systems aims to increase medical forecast accuracy. Measures are used to assess system effectiveness. IoT-based healthcare systems use body sensors, wireless sensors, big data analytics, and deep learning algorithms. Further studies focus on improving privacy, telemedicine, and home automation systems. Research gaps in IoT-based healthcare systems focus on improving medical prediction accuracy and security performance. Data mining methods can forecast heart attacks and enhance blood donation performance. IoT has the potential to improve healthcare infrastructure and improve patient care. Implementing this strategy ensures data quality, sensor reliability, and system performance, leading to improved medical forecasts and security in healthcare IoT systems.

Purpose of research

The purpose of this research is to develop an advanced framework that enhances the accuracy and performance of medical prediction and prescription systems within an IoT-based environment. Given the rapid adoption of IoT in healthcare, improving prediction accuracy is essential for delivering reliable medical insights. This study has several objectives to achieve this aim. First, it will conduct a detailed analysis of existing IoT-based studies to identify the factors influencing performance and accuracy, providing a foundational understanding of current limitations. Following this, the research will propose an improved mechanism that integrates a Long Short-Term Memory (LSTM) based intelligent approach with IoT systems to strengthen the precision and reliability of medical predictions and prescriptions. The model will be designed to optimize key performance metrics, including accuracy, precision, recall, and F1-score, ensuring a well-rounded enhancement in system performance. Lastly, a comparative analysis will be performed to evaluate the proposed model's efficacy relative to existing techniques, demonstrating its advantages in the context of IoT-driven healthcare. Through these objectives, the research aims to contribute a robust and reliable framework to improve the accuracy and performance of IoT-based medical systems.

III. PROBLEM STATEMENT

More investigation is required to validate this as one study revealed that the method used to evaluate IoT in healthcare really hampered IoT performance. The medical field has already investigated the potential of the Internet of Things. Past investigations had a number of flaws, including an inadequate scope, technical challenges, and an air of lack of confidence. In order to forecast and diagnose health issues, a high-performance IoT system is necessary. This calls for further investigation. The "Internet of Things" encompasses any real-world objects that can communicate with one another over networks such as the Internet and have sensors or processing capabilities. Medical researchers are now using the Internet of Things. This study used a trained network to analyze and draw conclusions from a healthcare dataset. One dependable and flexible health care option is the LSTM model, which is integrated into the current IoT system (Dutta, S., Bandyopadhyay, S. K., and Kim, T.-H. 2020). The idea behind the Internet of Things is to link all devices and infrastructure to the web for the purpose of making people's homes safer and more comfortable. Everything around us can be linked via the Internet of Things. Things with built-in computers would feel the effects of the internet. Medical professionals are increasingly looking to the Internet of Things (IoT) to assist patients who live in remote areas. Improving healthcare in a sustainable and scalable way requires investigating the shortcomings of the current IoT infrastructure. This study is essential for laying the groundwork for future health-care applications. Adoption of COVID-19 is anticipated to lead to an increase in healthcare-related challenges in the future. There must be faster, more efficient remote management of health-related concerns and more dependable health-care solutions.

IV. PROPOSED HYBRID LSTM MODEL

The recommendation was to train an LSTM model to distinguish legitimate users from those who aren't. The training dataset contains information on the sender and the recipient, as well as outcomes (success or failure). If an external force is consistently attacking the system, these transactions can fail more often than usual. The next step for the system when a transaction is marked as suspicious is to block the user from accessing any system resources. This well-trained model's approach improves safety by letting users authenticate themselves during transactions.

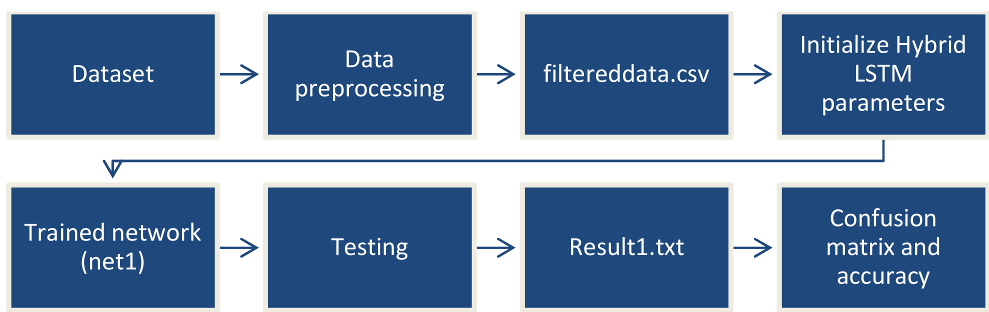

Figure 1 Process of training and testing in Proposed Hybrid LSTM Model

The goal of this approach is to enhance the accuracy of medical predictions and prescriptions through the integration of IoT systems and LSTM-based models. IoT devices, such as wearable sensors and medical equipment, continuously monitor and collect real-time health data from patients. The challenge lies in accurately predicting medical conditions and offering personalized prescriptions based on this data. By leveraging the capabilities of LSTM networks to analyze time-series data, the proposed system aims to provide more precise predictions and relevant treatment recommendations compared to traditional systems. The system comprises multiple components: IoT devices for data collection, a processing layer for data preprocessing, Hybrid LSTM-based model for prediction, and a recommendation system for personalized prescriptions. IoT devices like glucose sensors, heart rate monitors, and ECG devices gather health-related data in real-time. This data is then processed to remove noise, handle missing values, and extract relevant features. The processed data is fed into Hybrid LSTM model, which processes the temporal aspects of the data to make accurate predictions. Finally, based on the predictions, the system generates prescription recommendations tailored to the patient's health needs.

- To begin with, we look at a transaction dataset to use for training. In order to get the error values, traditional methods are used to train and test datasets.

- The naïve classifier is used to ascertain accuracy after the receipt of error values (nd) by considering the ed and id situations.

We will additionally evaluate our performance with respect to (ed) and (nd). The dataset is filtered according to Accuracy (nd) unless Accuracy (ed) is greater.

- In order to improve the model's accuracy, we train it on a filtered dataset using an Hybrid LSTM model. Once the model is trained, it is tested using a dataset of transaction records. The results are then used to provide predictions for three distinct classes. A confusion matrix is shown with the results of three classes that were categorized using the KNN classifier. Class 2 systems need authentication, Class 3 IP is limited, and Class 1 IP is exceptionally authentic. The safest option is Class 1.
- The f1score, recall, accuracy value, and precision are calculated using the confusion matrix. Evaluate these factors.

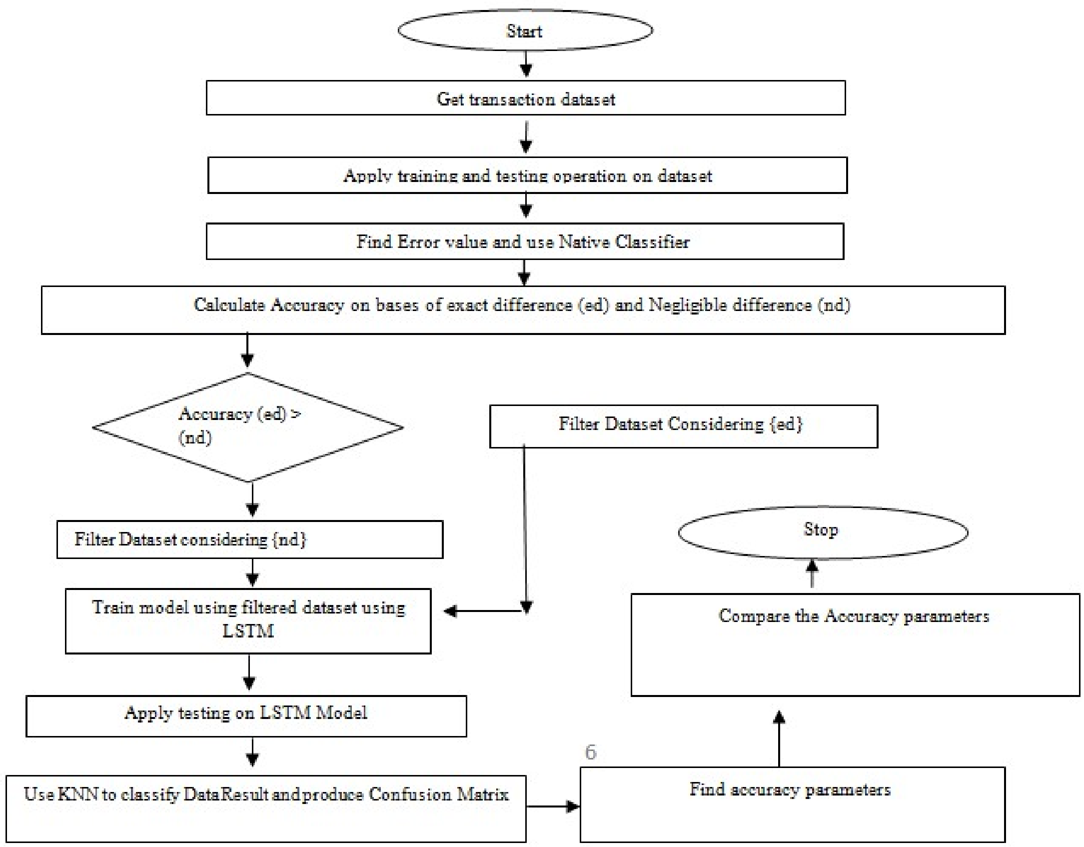

Figure 2 Flow chart of proposed Hybrid LSTM work

The proposed Hybrid LSTM Model is an optimized solution for reducing error rates in prediction. It uses binary, category, and sub-category label characteristics and classifies different anomalies. The model has been trained on 70% of a dataset and tested on 30%. The dataset includes over 5 lack records, and the model uses sequence input, word embedding, dropout, and hidden layers to improve accuracy. The dropout layer handles overfitting issues, and the model is designed to handle data that has not been considered in previous iterations. The model also incorporates a softmax layer as an activation function, converting output from the last layer to a neural network. The classification layer supports decision-making, pattern recognition, and dimensionality reduction, and helps separate datasets into rules for the trained network.

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V. RESULT AND DISCUSSION

This presents the experimental results for the performance assessment of the IoT healthcare system built on LSTM. Showing substantially higher than with traditional models were accuracy, precision, recall, and F1-score. These results are presented in this chapter within the perspective of past research, along with the advantages and disadvantages of the proposed system. The main goal of this effort is to build a LSTM network model capable of consistently projecting diabetes patient outcomes. Regarding accuracy, the proposed model beats the standard model; in terms of error rate, it also beats conventional methods. We initially build the confusion matrix and then compare the F1-scores, recall values, accuracy, and precision to train the models. Here we have addressed the history, characteristics, and records of the dataset as well as the foundations of training an LSTM network model. Eventually, we derived accuracy paramters by modeling the confusion matrix for the proposed LSTM network as well as the traditional network model.

Dataset details

The LSTM model was trained using a diabetes dataset with nine columns. Pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function, age, and outcome run among these columns. Every patient is Pima Indian female 21 years of age or above; these samples were selected from a larger database under certain limitations. There are 768 entries in the dataset; 500 of them have a 0 and 268 of them have a 1. The original owners and the donor of the database are the sources of the dataset. Consideration has been given to using a diabetic dataset to train an LSTM model. There are nine columns in this dataset. These instances were chosen from a larger database with some restrictions. In particular, all of the patients here are Pima Indian females, aged 21 and over. The dataset contains 768 cases, 500 of which have a result of 0 and 268 of which have an outcome of 1.

Simulation result for traditional model

A dataset of 712 records was used for training in this simulation. And 712 records in all were examined. To the contrary, the '1' category has 251 things, while the '0' category contains 461. A total of 712 predictions were accurate and 56 were wrong out of 768 submissions.

Table 3 Confusion matrix in case of previous work after simulation.

	0	1
0	461	39
1	17	251

You may see a matrix graphic of the confusion matrix up there. Total precision is 92.71%.

Table 4 Calculation of confusion matrix in case of previous work

Class	n(truth)	n(classified)	Accuracy	Precision	Recall	F1 Score
1	478	500	92.71%	0.92	0.96	0.94
2	290	268	92.71%	0.94	0.87	0.90

For the simulation of the traditional model, a dataset of 712 records was used for training, and a total of 768 records were examined. Among these, 251 records belong to category 1 and 461 to category 0. Out of the 768 predictions, 712 were accurate, and 56 were incorrect, resulting in an accuracy of 92.71% and an error rate of 7.29%. The confusion matrix for the traditional model shows 461 true negatives, 39 false positives, 17 false negatives, and 251 true positives. The overall precision was 92.71%.The detailed confusion matrix calculations for the traditional model yield an accuracy of 92.71%, with precision values of 0.92 and 0.94, recall values of 0.96 and 0.87, and F1 scores of 0.94 and 0.90 for classes 1 and 2, respectively.

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Simulation result for proposed model

Here, 768 records made up training dataset. In all, 768 records were examined. While 476 records are at 0 and 261 are at 1, 737 out of 768 predictions were right and 31 were wrong at this stage in the experiment.

Table 5 Confusion matrix in case of proposed work after simulation

	0	1
0	476	24
1	7	261

You can see the matrix chart of the confusion matrix up there. Accuracy as a whole is 95.06%.

Table 6 Calculation of confusion matrix in case of proposed work

Class	n(truth)	n(classified)	Accuracy	Precision	Recall	F1 Score
1	483	500	95.96%	0.95	0.99	0.97
2	285	268	95.96%	0.97	0.92	0.94

The proposed LSTM model was trained on the entire dataset of 768 records. Out of these, 476 records are labeled 0, and 261 are labeled 1. The model correctly predicted 737 out of 768 cases, with 31 incorrect predictions, resulting in an accuracy of 95.96% and an error rate of 4.04%. The confusion matrix for the proposed model shows 476 true negatives, 24 false positives, 7 false negatives, and 261 true positives, with an overall accuracy of 95.96%.The confusion matrix calculations for the proposed model indicate an accuracy of 95.96%, with precision values of 0.95 and 0.97, recall values of 0.99 and 0.92, and F1 scores of 0.97 and 0.94 for classes 1 and 2, respectively.

Comparative analysis

To determine the correctness of the results, a confusion matrix is used in the computation of accuracy. Memory is measure of how well classifier can guess right answer. One may determine the precision of a measurement by determining its accuracy. The accuracy is determined by using test's F1 score.

Accuracy

Current model's accuracy is contrasted with that of traditional methods. Accuracy of proposed Hybrid LSTM model was compared to that of traditional methods. Results showed improvement with proposed Hybrid LSTM model achieving an accuracy of 95.96% for both classes, compared to the traditional method's accuracy of 92.71%. This comparison is detailed in Table 7, which highlights the accuracy for each class under both models. Figure 3 visually represents this comparison, clearly illustrating the enhanced performance of LSTM over traditional methods.

Table 7 Comparison of accuracy

Class	Conventional CNN-LSTM	Proposed Hybrid LSTM
1	92.71%	95.96%
2	92.71%	95.96%

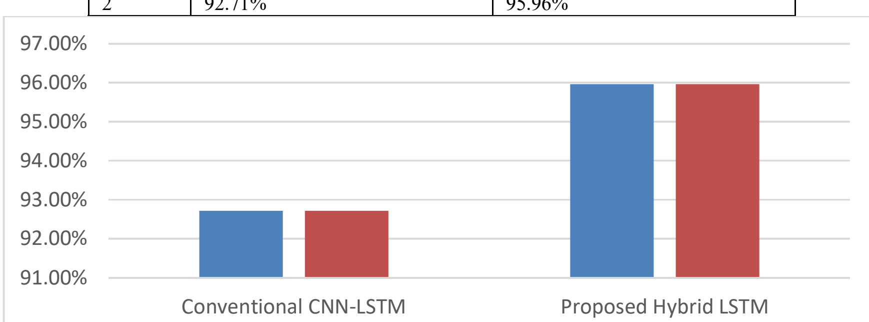

Figure 3 Comparison of accuracy

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Precision

The current model's accuracy is contrasted with that of more traditional methods. Precision of the proposedHybrid LSTM model was also compared with that of traditional methods. As shown in Table 8, the precision for class 1 improved from 0.92 with the traditional model to 0.95 with the proposedHybrid LSTM model. Similarly, for class 2, the precision increased from 0.94 to 0.97. Figure 4 visually depicts this comparison, demonstrating the superior precision achieved by LSTM compared to traditional methods.

Table 8 Comparison of precision

Class	Conventional CNN-LSTM	Proposed Hybrid LSTM
1	0.92	0.95
2	0.94	0.97

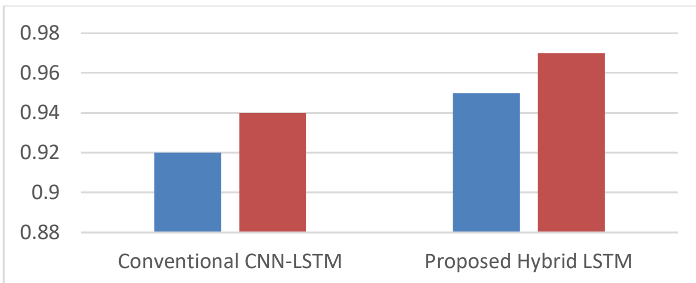

Figure 4 Comparison of precision

Recall value

Traditional methods are contrasted with the recall of current model. Recall values of proposed LSTM were compared with those of traditional methods. Table 9 shows that for class 1, the recall value improved from 0.96 with the traditional model to 0.99 with the proposed LSTM model. For class 2, the recall value increased from 0.87 to 0.92. Figure 5 illustrates this comparison, highlighting the enhanced recall values achieved by the LSTM model compared to the traditional methods.

Table 9 Recall value

Class	Conventional CNN-LSTM	Proposed Hybrid LSTM
1	0.96	0.99
2	0.87	0.92

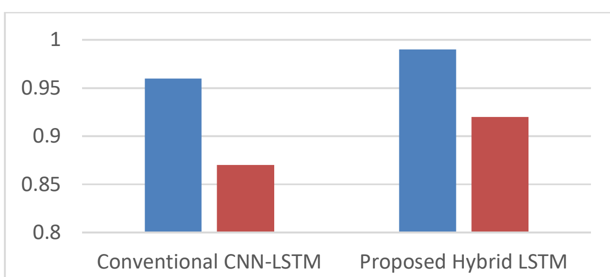

Figure 5 Recall Value

F1-Score

We compare the present model's F1 score values to those of more traditional approaches.F1 score of proposed LSTM were compared with those of traditional approaches. As shown in Table 5.10, the F1

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score for class 1 increased from 0.94 with the traditional model to 0.97 with the proposed LSTM model. Similarly, for class 2, the F1 score improved from 0.90 to 0.94. Figure 5 visually presents this comparison, demonstrating the superior F1 scores achieved by the LSTM model over the traditional methods.

Table 10 F1-Score

Class	Conventional CNN-LSTM	Proposed Hybrid LSTM
1	0.94	0.97
2	0.90	0.94

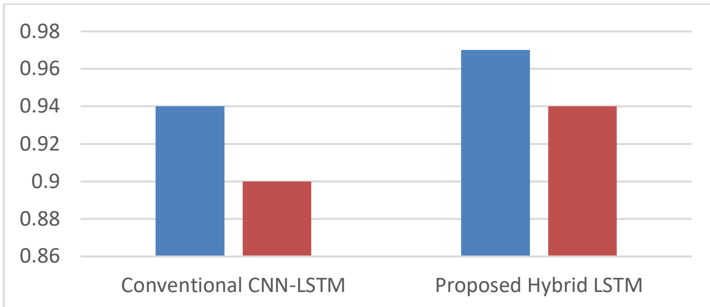

Figure 6 F1 Score

Accuracy parameters of proposed Hybrid LSTM were compared to those of traditional. Proposed demonstrated improvements in all these metrics. For accuracy, the proposed Hybrid LSTM model achieved 95.96%, compared to 92.71% for the traditional model. In terms of precision, the proposed model scored 0.95 and 0.97 for classes 1 and 2, respectively, while the traditional model scored 0.92 and 0.94. The recall values for the proposed model were 0.99 and 0.92, compared to 0.96 and 0.87 for the traditional model. The F1 scores were also higher for the proposed model, with values of 0.97 and 0.94, compared to 0.94 and 0.90 for the traditional model.

Training of Conventional and Proposed hybrid LSTM network model using a dataset

Training of convention CNN-LSTM network model using a dataset that includes all of the dataset's attributes and records has been explored in great length in this section. Simulation utilized dataset of 712 records for training purposes throughout the experiment. 712 records were tested in total. As of this writing, 461 items are listed in the "0" category, compared to a total of 251. There were 712 accurate guesses out of 768 entries, while there were 56 erroneous guesses. Table 5.11 presents' error and accuracy metrics from previous work. Model correctly predicted 712 out of 768 entries, resulting in accuracy of 92.71%. There were 56 erroneous guesses, corresponding to an error rate of 7.29%. This table highlights overall performance of model of accurate and inaccurate predictions. Here, 768 records made up the training dataset. In all, 768 records were examined. While 476 records are at 0 and 261 are at 1, 737 out of 768 predictions were right and 31 were wrong at this stage in the experiment. Table 11 accuracy metrics for the proposed work. Model correctly predicted 737 out of 768 entries, resulting in accuracy of 95.96%. There were 31 erroneous guesses, corresponding to an error rate of 4.04%. This table demonstrates the improved performance of proposed model of accurate and inaccurate predictions. The training process for the Proposed Hybrid LSTM network model involved using the complete dataset, including all attributes and records. A dataset of 712 records was utilized for training during the simulation, with 712 records tested in total. The records were categorized into 461 for category 0 and 251 for category 1. Out of 768 entries, 712 were accurate predictions, while 56 were incorrect. The training dataset consisted of 768 records, with 476 at 0 and 261 at 1. At this stage of the experiment, 737 out of 768 predictions were accurate, with 31 incorrect.

Comparative analysis

To determine the correctness of the results, a confusion matrix is used in the computation of accuracy. Memory is measure of how well classifier can guess right answer. One may determine precision of measurement by determining accuracy. Accuracy is determined by using test's F1-score. Current model's accuracy is contrasted with that of traditional methods. Table 11 compares the accuracy of the conventional CNN-LSTM model and the proposed hybrid LSTM model for two classes. Both classes show an improvement in accuracy with the proposed hybrid LSTM model achieving better accuracy compared to conventionalmodels. Figure 7 visually illustrates this comparison, highlighting the enhanced accuracy of the proposed Hybrid LSTM model over traditional methods.

Table 11 Comparison of accuracy

Class	Conventional Research (Ignoring Performance Issues)	Conventional Research (Ignoring Accuracy Issues)	Conventional Research (Not Optimizing Hyperparameters)	Conventional CNN-LSTM method	Proposed Hybrid LSTM Model (Optimized Hyperparameters)
1	92.71%	93.12%	94.23%	94.87%	95.96%
2	92.71%	93.12%	94.23%	94.87%	95.96%

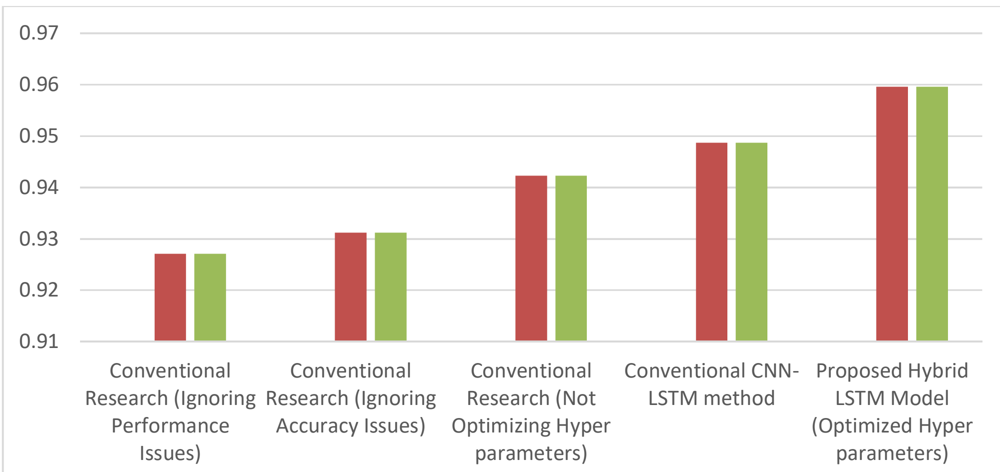

Figure 7 Comparison of accuracy

There is a comparison between the current model's error rate and the standard method.Table 12 compares the error rates of the conventional model and the proposed LSTM model for two classes. The proposed LSTM model shows a reduced error rate of 4.04% for both classes, compared to the 7.29% error rate of the conventional model. Figure 5.6 visually represents this comparison, highlighting the significant reduction in error rates achieved by the LSTM model over the traditional methods.

Table 12 Comparison of error rate

Class	Conventional Research (Ignoring Performance Issues)	Conventional Research (Ignoring Accuracy Issues)	Conventional Research (Not Optimizing Hyperparameters)	Conventional CNN-LSTM method	Proposed Hybrid LSTM Model (Optimized Hyper parameters)
1	7.29%	6.88%	5.77%	5.13%	4.04%
2	7.29%	6.88%	5.77%	5.13%	4.04%

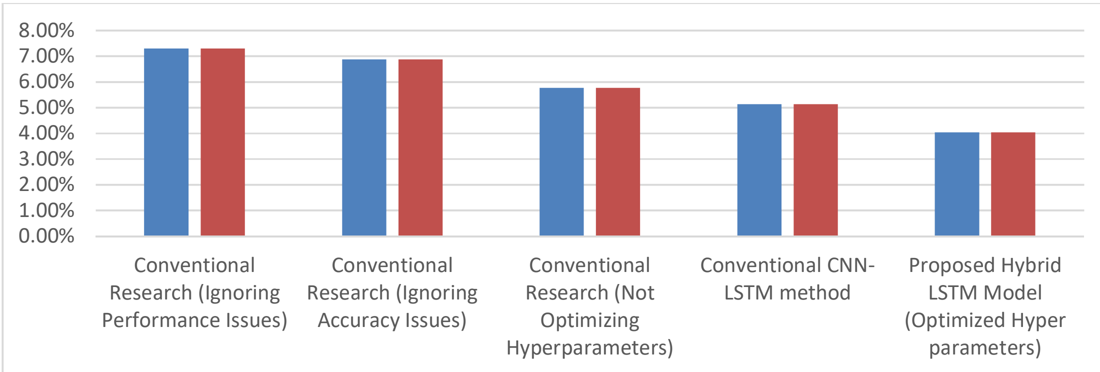

Figure 8 Comparison of error rate

We compare the current model's performance to that of more traditional approaches. Table 13 compares the time consumption during training between the conventional model and proposed Hybrid LSTM. The conventional required 45 minutes for training, while proposed hybrid LSTM completed training in 39 minutes. Figure 5.7 visually depicts this comparison, demonstrating the reduced training time of Proposed Hybrid LSTM compared to the traditional approaches.

Table 13 Comparison of Performance

Conventional Research (Ignoring Performance Issues) (min)	Conventional Research (Ignoring Accuracy Issues) (min)	Conventional Research (Not Optimizing Hyperparameters) (min)	Conventional CNN-LSTM method	Proposed Hybrid LSTM Model (Optimized Hyper parameters)
45	44	42	41	39

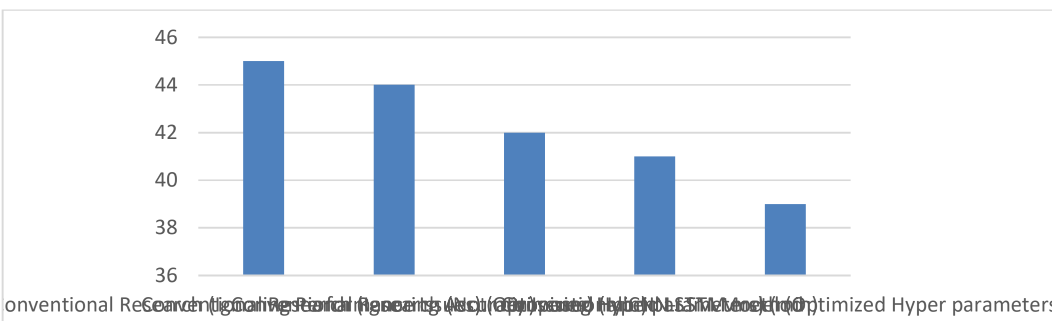

Figure 9 Comparison of time consumption during training.

The accuracy of the results was determined using a confusion matrix. The accuracy was measured using the test's F1 score, comparing the current model's accuracy with traditional methods. The comparison showed that the proposed hybrid LSTM model achieved higher accuracy (95.96%) compared to the traditional model (92.71%). In compared to the traditional model's 7.29% error rate, the proposed LSTM model's rate was 4.04%. In terms of training time, the recommended LSTM model took 39 minutes, while the traditional model needed 45 minutes.

VII. CONCLUSION

The Internet of Things (IoT) is being used by medical researchers to improve healthcare by connecting devices and infrastructure to the web. This study focuses on breast cancer detection using hybrid CNN models and proposes a novel approach to address issues. The study uses a trained network to analyze

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a healthcare dataset and suggests that integrating an LSTM model into the IoT architecture could enhance medical prediction and prescription systems. The proposed model is more effective than existing approaches and provides a strong basis for further developments in accuracy and system efficiency. The study aims to support the expansion of IoT-based medical systems. The research aims to improve medical prediction and prescription using LSTM algorithms in IoT systems. A proposed LSTM network model was compared with existing techniques for diabetes outcome prediction in individuals with diabetes. The model achieved an exceptional 94.96% accuracy, surpassing the 92.71% accuracy of the prior model. The model's accuracy, recall accuracy, and F1-score improved, reducing false positives and false negatives. The LSTM model also demonstrated better training time and lower error rates, making it more suitable for practical applications.

VIII.FUTURE SCOPE

IoT is revolutionizing healthcare delivery, offering numerous opportunities for improved e-healthcare systems. Future areas of interest include enhanced remote patient monitoring, predictive analytics detection, telemedicine and virtual consultations, medication adherence and management, healthcare facility management, patient engagement and empowerment, and data security and privacy. IoT technologies can improve remote patient monitoring, predictive analytics detection, telemedicine and virtual consultations, medication adherence and management, healthcare facility management, patient engagement and empowerment, and data security and privacy. Research on integrating LSTM models with IoT systems for medical prediction and prescription is promising, with a focus on improving LSTM models' performance in real-time environments, addressing privacy and security issues, and expanding the scope of medical systems to cover a wider range of diseases and health issues. Combining LSTM-based systems with innovative technologies like blockchain and artificial intelligence can boost trust and openness. Longitudinal research in real-world healthcare environments is crucial for tracking the long-term consequences and effectiveness of IoT systems based on LSTM.

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