EDRAAK
Vol. (2024), 2024, pp. 8–17
ISSN: 3078-8412

Research Article

Deep Learning-Driven Disease Prediction System in Cloud Environments using a Big Data Approach

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ARTICLE INFO

Article History
Received 9 Oct 2023
Revised: 2 Des 2023
Accepted 2 Jan 2024
Published 23 Jan 2024

Keywords
Big Data Systems,
Disease Prediction,
Cloud,
Deep Learning,
Machine Learning.

ABSTRACT

Disease detection has gained great significance in the big data cloud systems as health organizations try to accrue manifold benefits from massive amounts of data to achieve better outcomes in patients. The ability to detect diseases with better efficiency can achieve timely interventions, better resource allocations, and enhanced treatment strategies. However, there are several challenges with the implementation of such systems regarding the integration of different kinds of data, handling imbalanced datasets, and ensuring that real-time processing is capable of supporting clinical decisions. This paper addresses these challenges by proposing a novel disease prediction model on a cloud environment, incorporating the strengths of both Recurrent Neural Networks and Convolutional Neural Networks. The proposed RNN+CNN-based model can effectively capture temporal dependencies and spatial features from different data sources, like medical images and time-series patient data. This model has given improved results through extensive experimentation with different key evaluation metrics like accuracy, precision, recall, F1-score, and AUC-ROC, which are quite higher than other disease prediction systems. Besides, the proposed model is optimized for light speed in inference times, reaching an incredible processing speed of 0.4 seconds per prediction. Thus, the Big Data approach provided within the cloud infrastructure will ensure the predictability and accessibility without bounded local computational resources, opening advanced predictive analytics capabilities to healthcare practitioners.

1. INTRODUCTION

The IoT is a technological paradigm where physical objects are connected to the Internet and communicate with each other to functionally create one cohesive system. The IoT paradigm displaces the notion that the burden of computation should fall only with high-performance devices such as laptops, servers, and high-end smartphones [1]. Rather, it talks to how capability should be integrated into smaller and sometimes inane objects like smart watches, sensors, and even vehicles which exhibit intelligence. These, on the other hand, are relatively weak devices which create a network-known as IoT-this networking communicates, processes data, and decisions independently

At the same time, with sensors, actuators, and processors embedded in modern IoT objects, hardware obviates human interference in most situations, further creating intelligent environments. It means that electronic devices have come a long.

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DOI: https://doi.org/10.70470/EDRAAK/2024/002

way from their limited one-function origins and are now able to multitask, receive inputs from humans or other systems, and process this information to create relevant outputs [2]. In some cases, for example, the machine can monitor its own activities to know, say, how many resources have been consumed or how many are remaining to arrive at decisions efficiently without human intervention.

Therefore, machine learning helps to make smart IoT systems capable of making better decisions. As a result of IoT machines generating voluminous data from different sources in real time, machine learning algorithms analyze the same for obtaining meaningful insights for optimizing decisions [3]. The Data Analysis Matching Process is important in the case to align such data to areas of interest, such as speed prediction and handling volumes within neural network models through classification and regression tasks.

Since data comes from a broad variety of sources, it necessarily develops advanced analysis techniques in handling properties that differ in streams of data [4]. This is crucial for efficiency within the IoT ecosystem, where scalability, speed, and optimization of data models are common pain points. In simple words, an IoT device has to process data from multiple inputs at high speed while the output should be precise and useful. The volume of data in IoT systems serves to underline the demands on robust models that can scale demands while making real-time decisions with efficacy.

Machine Learning is the fastest-growing area related to data mining, but again they differ in their focus. Data mining generally relates to the study and analysis of datasets in order to find patterns and trends, which might also be called unsupervised learning [5]. In contrast, machine learning encompasses many other techniques. Unsupervised learning falls under machine learning, in which the system detects pattern and structure in data-without requiring labeled outcomes from the data-so that it can establish a baseline of behavioral profiles across entities.

Once these profiles are set, their associated machine learning algorithms will detect anomalies or variance from that norm as abnormal behavior [6]. That becomes especially useful in situations where large volumes of unstructured data have to be put in some order or where patterns are not necessarily obvious. In a nutshell, this is machine learning in such contexts: automatically having insights where the systems themselves evolve and improve their decision-making processes over time without intervention.

In the larger world of data analysis, machine learning applies to complex model creation and algorithms that power predictive analytics-what some in business would call prescriptive analytics. These models predict what will happen in the future based on historical data [7]. Equally, with these models, companies are able to make appropriate, repeatable, and accurate decisions. Predictive capabilities in machine learning rely heavily on identifying patterns and correlations within past data to predict future behavior. Machine learning models may be trained on large datasets of historic trend data, for example, to make forecasts across industries, including finance, retail, and health.

As such, data scientists, engineers, and analysts employ such models to uncover insights from data that may not be so obvious through traditional statistical methods. It is in identifying these unseen patterns that machine learning lets the organization act upon the data-driven predictions that would otherwise have gone completely unnoticed. Because machine learning can learn from data and improve predictions over time, the concept has become a key driver in today's analytics landscape.

The work described here leveraged a large, complex data set comprising images, text, and sensor readings captured from IoT devices that were stored in the cloud to access them with minimal latency. In all, cloud computing supplements the IoT with infrastructure to manage and process the going stream of information produced by IoT devices. In this respect, machine learning algorithms classify data into "normal" and "affected" classes [8]. As such, binary classification is warranted when one has to operate scenarios involving anomaly detection where the system shall identify conditions of standard operation from those conditions which require attention or intervention.

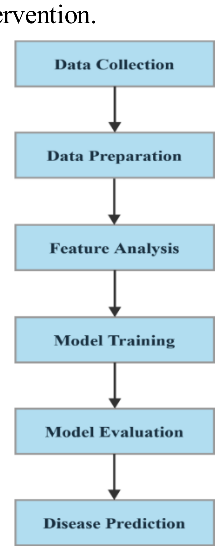

Fig. 1. Typical flow of machine learning driven disease prediction model

With the introduction of Artificial Intelligence, the incoming data will be mapped by the system and processed in a manner to enable its prompt classification. Putting together IoT, machine learning, and cloud computing creates an ecosystem where intelligent decisions may be taken in real time, largely improving the operational efficiency in various applications, spanning from smart homes to industrial automation [9]. With this, IoT continued to evolve with innovation opportunities improving user experiences across diverse domains.

These same models can also predict the minutes that patients will spend in each stage of the visit and, therefore, inform the hospitals on how to triage the patients and manage the resources to reduce the wait times. It will take into consideration a wide array of variables, including the type of treatment needed, availability of doctors and diagnostic equipment, and previous history for better predictions of the journey of the patient inside the hospital.

It minimizes the bottlenecks in the system, increases patient satisfaction with minimal wait time, and optimizes the use of medical personnel and equipment. Examples include the integration of machine learning into patient queue management systems for better solutions of complex operational challenges in healthcare, ultimately improving the overall experience of both patients and providers [10]. Machine learning is then very important in modern healthcare since it transforms the huge amount of data created from both patients and operations into actionable insight that drives efficiency and improves patient outcomes.

2. RELATED WORKS

Machine learning has numerous applications, and hence, finds great momentum in all areas where large datasets are used and the prediction capability forms the basis of analysis. In general, machine learning has emerged from being largely an academic discipline into a practical tool for solving real-world problems over the years. It was one of the crucial areas of its impact, wherein the algorithms of machine learning reveal hidden patterns in large datasets, coming up with data-driven predictions. Predictably, analytics will bear considerable importance in all information-intense industries, such as health care, finance, retail, and manufacturing.

The flexibility of machine learning [11] was in the fact that it could work with structured and unstructured data, and solutions ranged from relatively simple linear models up to complex deep learning architectures. With big data and computational power available, machine learning could solve at this moment problems which earlier appeared too complex or required too much time. While machine learning models have supplanted much decision-making in many cases, they do indeed make it possible for businesses and other organizations to automate processes, make better decisions more accurately, and unlock insight into their work that might have been hidden by taking more traditional approaches.

The most prominent application of Predictive Analytics in Healthcare through machine learning is yet to be extended. It is because the nature of these flows is inherently so complex that their waiting times are difficult to predict at a hospital level in health systems. These algorithms in machine learning would sift through big volumes of information on the patients' past history, present symptoms, and treatment needs to make predictions of the course of action that is in the future with respect to the patient for optimization of medical resource allocation [12]. This becomes all the more vital in the case of overcrowding which confronts all major hospitals, in as much as the queue management has to be appropriately organized to ensure timely patient care. Conventional queue handling procedures have little scope in handling patient queues considering the uncertainties that are there in medical conditions and treatment time for various procedures and programs.

The applications of machine learning are not restricted to predictive analytics in healthcare. The unsupervised learning technique of machine learning is very potent in abnormal pattern and anomaly detection from datasets. This will be about domains related to cybersecurity, fraud detection, and network security; unsupervised learning algorithms should, in turn, be used to identify anomalies that show some kind of threat. Other than supervised learning, which is based on labeled datasets, unsupervised learning does not need any predefined outcome, which makes it useful when the patterns are either unknown or the dataset is too big to label by hand. Various unsupervised learning models establish baseline behavior profiles and are capable of flagging significant anomalies as deviations from the norm. Being able to detect outliers or rare events is extremely important in several areas where operational security and integrity need to be maintained.

Business and financial uses of machine learning vary, from customer segmentation to risk analysis down to financial forecasting. Predictive models used in these industries utilize past information ranging from transaction records to individual customer behavior for the prediction of future trends. It applies machine learning algorithms in improving customer experience, marketing strategies, and managing risks by predicting market fluctuation or fraud activities [13]. Predictive analytics has been quite helpful in that respect; thus, enabling organizations to make evidence-based decisions with data-driven predictions. This reduces uncertainty and thus allows any business to be one step ahead of the game since they are prepared for a shift in consumer behavior or market conditions.

Besides, the role of machine learning in data mining simply cannot be overestimated. Data mining is absolutely about extracting useful insights from the heap of information, and a data mining process enriched with machine learning indeed automates the detection of patterns and relationships from data. It is very important in retail industries, where knowledge of consumer behavior-through data mining-can facilitate very specific marketing and personalization for customers [14]. These models of machine learning are designed to address the complexity of big data with regards to handling large volumes of

information much faster and more accurately. In this regard, integrating machine learning with data mining will allow businesses to gain insights into customer preference, product performance, and market trends more effectively.
In general, this adaptability of machine learning to learn from data is so attractive that it cannot be missed in several fields. Applications involve healthcare, cybersecurity, finance, and retail, where its predictive capabilities help organizations arrive at smarter, more informed decisions [15]. The ever-growing reliance on machine learning is representative of its potential for unlocking secret insights in a large amount of data, improving efficiency by automating even the most difficult tasks. This technology is continuously improving, and further integration with emerging fields like artificial intelligence, big data analytics, and cloud computing will continue to develop its capabilities, making industries function not just better but smarter, right from decision-making perspectives to a wide gamut of industries. Machine learning stands on both a theoretical and practical perspective to continue driving innovation in solving many of the complex problems of modern times.
The field of machine learning-driven disease prediction systems in cloud environments, using a big data approach, is full of research opportunities and gaps. While significant developments have taken place in the applications of machine learning models for predicting diseases based on huge datasets, there are still some limitations with respect to scalability, accuracy, and integration of the system in real-world healthcare settings. One of the prominent gaps is how to deal with heterogeneous data types, usually gathered from cloud-based healthcare environments [16]. The medical data normally takes on various forms such as structured data in the form of lab results and vital signs, unstructured data in the form of doctor's notes or images, and real-time streaming data from Internet-of-Things devices in wearable sensors. Although voluminous data can surely be handled by large-scale machine learning models, many of them fail to integrate these types of data in ways that realize maximum predictive accuracy. In real-time applications, developing models that can seamlessly integrate multi-modal data sources is still a challenge that researchers are pursuing.
Another major gap involves the security and privacy concerns of cloud environments. While cloud computing enables scalable, easily accessible resources for big data analytics, it also opens up a whole set of potential insecurities with sensitive medical data. Ensuring patient information privacy in the use of cloud-based machine learning systems is an urgent unresolved issue. At this time, all encryption and machine learning methods that preserve privacy-including federated learning-are still in a development phase, and few comprehensive solutions balance data security against real-time disease prediction. Further research will be required into more robust methods of preserving privacy, including improved encryption algorithms, along with enhanced federated learning techniques that can be used within healthcare contexts.
Any disease prediction system needs to improve the interpretability and explainability of the machine learning algorithms, thereby gaining trust and wider adoption in clinical settings. This would mean developing techniques that will help medical professionals gain insight into why a particular decision has been made, enhancing transparency and confidence in automated systems. Whereas AI methods [17] at present are still in their infancy, much more research is needed in developing models that will result not only in accurate predictions of diseases but also give understandable reasoning for their decisions.
Another gap in the current research is scalability in deploying machine learning models to large-scale health systems. Most of the machine learning-based disease prediction systems that have been developed so far have been validated on small or limited datasets, which are not representative of huge diverse datasets generated in real-world cloud environments [18]. The scalability challenge of the models toward big data is thus a huge concern regarding their applicability with high accuracy and good performance. Most of the systems do not take into consideration the dynamics of health data, which is a state of continuous change and updating. This might challenge traditional models of machine learning, since most of them cannot adapt to new data in real time, resulting in outdated predictions of reduced efficacy. Interoperability, specifically, is a major challenge since most cloud-based health information systems use proprietary data formats and standards that make the integration of machine learning models across different healthcare providers or systems or regions difficult. The challenge that needs immediate attention is the capability of machine learning models to acquire data from various data sources without compatibility issues. Besides, the deployment of standardized frameworks regarding disease prediction models in a cloud environment is still in its infancy stage and makes the implementation of the systems by healthcare providers pretty complicated.

3. PROPOSED METHOD

Big data design in the proposed RNN+CNN-based disease prediction system in cloud environments is performed to reap the strengths of RNN and CNN in handling big volumes of complex textual healthcare data. The system is designed to manage and analyze textual data, including electronic health records, patient histories, real-time data from IoT devices, clinical notes, among other forms of structured and unstructured text data that might be useful in valid disease prediction. Textual data constitutes a major portion of the available information on patients in healthcare, unlike most of the models focusing on image processing.
Lab results, medical prescriptions, doctor observations, diagnosis reports, and live sensor data from wearable may form a part of all this. Such data is heterogeneous and voluminous; handling such data in order to extract meaningful insights from these different types of text and sequences holds a challenge. It is in this context that the integration of RNNs and CNNs comes in handy. RNNs, especially LSTMs, efficiently process data in sequence. That is very useful for finding patterns

across time in longitudinal healthcare records. Patient health records are mostly temporal data; development of certain symptoms or responses against various treatments may indicate an imminent problem in health. These temporal dependencies are captured by the LSTMs, thereby providing insight into how the condition of the patient has evolved over a period of time, hence making them appropriate for disease progression analysis based on historical text data.

Conventionally used in image processing, CNNs have equally been of great strength in text classification and feature extraction. In such a context, CNNs detect key patterns from textual data, like key terms about the patient's condition, or even anomalies from structured text formats. Convolutions on word embedding or sentence structures are made by CNNs with the intent of capturing n-gram features indicative of risk or disease markers. Using these convolutional layers, the CNNs can learn the local dependencies effectively, for example, the symptoms mentioned in a medical note, or perhaps the trends about laboratory test reports, so important in predicting any disease. These features are then extracted and pooled to result in compact high-level representations of text, rich in diagnostic information.

This paper proposes that the RNN+CNN-based big data disease prediction system in a cloud environment assumes the major role in terms of bringing out the strengths of both recurrent neural network and convolutional neural network in processing various complex health information. This hybrid architecture will overcome the deficiencies of the existing models for cloud-based healthcare by marrying the sequential data-handling capability of RNN with the power of feature extraction and spatial data processing capabilities of CNN to ensure an accurate, scalable, and real-time disease prediction.

The different contributors of healthcare information are first ingested into this system's cloud environment. This is quite important in handling huge volumes and varieties of big data in the modern healthcare setting. It automatically scales up the backend infrastructure when more data is being created and processed, providing the needed computational power and storage for big data analytics on such a system. It will hold both structured data, such as electronic health records and lab test results, and unstructured data, such as doctors' notes and medical reports, real-time data from wearable or other IoT sensors that monitor patient vital signs continuously. These streams of data then undergo preprocessing to have uniformity and accuracy; this will involve normalizing, replacing missing values, and transforming the data into neural network-compatible formats.

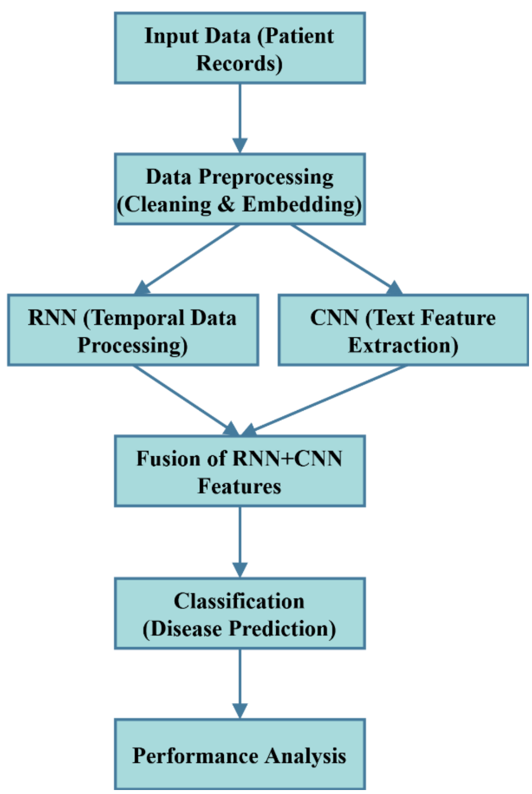

Fig. 2. Flow of the proposed disease detection system

This cloud infrastructure can further be enabled to continuously feed data into this system for real-time updates of patient information. The next step after collecting data is pre-processing, which consists of cleaning the data, tokenizing, and bringing the data into a structured format valid in deep learning models. This involves text preprocessing, which means the conversion of raw text into numerical representations such as word embeddings, which is needed by both RNN and CNN for effective processing of input data.

After preprocessing, the processing of sequential textual data will be performed by the RNN component. These might be, for example, that records have been maintained over a patient's time, mapping the history of blood pressure, glucose level, and symptoms of fatigue and shortness of breath. In such cases, the RNN would try to catch any pattern in these medical histories that could lead to disease. This is because the LSTM units in RNN remember information from past records and thus can process new entries. The model, therefore, learns from the trend of the patient's health data. It is, therefore, an ability to learn long-term dependencies that makes RNNs especially suitable for temporal pattern recognition in sequences of data. Various examples include the prediction of chronic conditions, the time of appearance of disease states such as diabetes and cardiovascular disorders given historical patient data.

This is done while the CNN works alongside it, taking in the same textual data. Still, CNN focuses on other features of interest that may not be temporal but are important to predict diseases. This may implicate analyzing volumes of clinical notes, descriptions of lab tests, or diagnostic reports for keywords or outlined medical conditions from the text. In turn, the CNN convolutional layers will use filters over the text data that may capture the essential medical terms, symptoms, or diagnoses, just as CNNs capture the spatial features in data. These patterns will be used to make it possible for the CNN to extract relevant features, such as those symptoms that are mentioned more frequently, to indicate a disease. It will then undergo pooling, after feature extraction, to reduce the extracted features into a high-dimensional vector representative of the text data meaningful elements.

Once the processing of inputs by both RNN and CNN is done, their features are fused in order to form one single comprehensive representation regarding the patient's health status. Such fusing of features would finally enable the system to combine the temporal insights of RNN with the text feature representation coming from CNN and provide a much richer and complete picture of the status of a patient. In cases where an RNN detects a degrading trend over time in the patient's health records, and when the CNN detects crucial terms in recent doctor notes indicative of a certain diagnosis, it can be taught that the combined model predicts with a great deal of accuracy a patient's likelihood of developing a certain disease. This multi-layer analysis increases the system's ability to learn deep relationships from data and hence make well-informed predictions.

Later, the features are fused and sent through a fully connected layer for classification purposes, where decisions on the risk for a certain type of disease for the patient are made. The output could be binary-for instance, "disease" or "no disease"-or it could involve multi-class predictions where the system evaluates the likelihood of a number of diseases based on input data. This classification layer takes as input the deep features coming from both the CNN and the RNN to make sure that any kind of prediction is informed by an in-depth analysis of the textual data. The system continuously learns and improves, helped by feedback loops and updates from the cloud, updating the system for better prediction as more data come in.

The proposed RNN+CNN-based disease prediction system in the cloud is the most powerful approach to handle large-scale textual health-care data. This approach will leverage the sequential data processing capability provided by RNN and the feature extraction capabilities provided by CNNs in conducting the analysis on diverse forms of health-care data, which range from time-dependent patient histories to unstructured clinical notes. The presented hybrid architecture allows the implementation of effective real-time disease prediction in cloud-based environments that allow for high-throughput architectures, making possible better patient outcomes and management of healthcare. The scalability of the cloud-based computing infrastructure is indeed overwhelming as it is able to run big data at high-speed performance, continuous updates, and keep health professionals updated with the most current and actionable insights.

4. RESULTS AND DISCUSSION

Figure 3 compares the accuracy of five available diseased prediction systems with the proposed approach using RNN+CNN. Accuracy is one of the primary measures to tell the performance of a model, which is described as a percentage of correctly predicted instances against the total instance. The five existing systems run different accuracies, whereby existing model performs the best at 85%. Yet, it is of importance to note that such a value, despite its impressiveness, does not fully reflect the model performance in classifying disease cases, especially in situations when there is some kind of imbalance in the datasets. On the other hand, the proposed RNN+CNN system demonstrates great improvement in accuracy results as high as 98%. This is understandable considering the fact that this kind of hybrid architecture is more efficient for the extraction of both temporal and spatial features.

Figure 4 shows the precision comparison of the same existing systems against the proposed RNN+CNN model. Precision is, by definition, the ratio of the number of true positive predictions to the total number of predicted positives and is important in contexts where the consequences of false positives are high. The precision of the state-of-solution systems varies within this analysis, with existing approach yielding a precision of 80% to show that it has a fair balance of true positive predictions against the false positives. However, the proposed RNN+CNN system in this work is able to yield an impressive precision value of 97%. Enhanced possibilities to reduce false positives instill trust in the outcome of predictions, hence quite appropriate for use in clinical applications where the perfection of diagnosis is prime. This performance suggests that the proposed method has enhanced the performance in not only prediction but has also provided an actionable output for healthcare professionals.

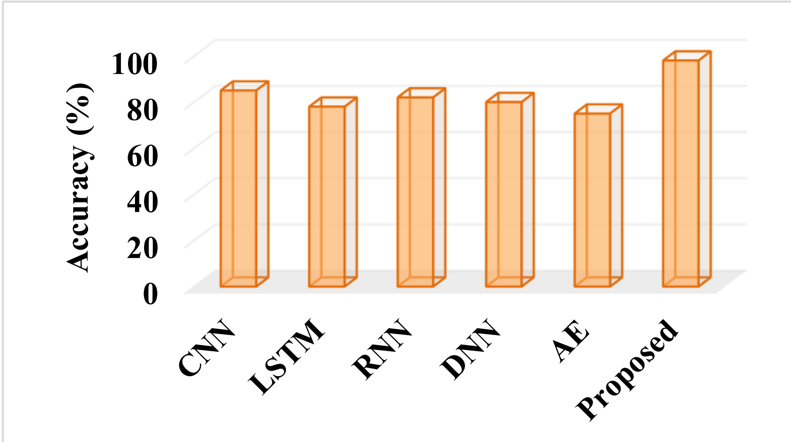

Fig. 3. Accuracy comparison

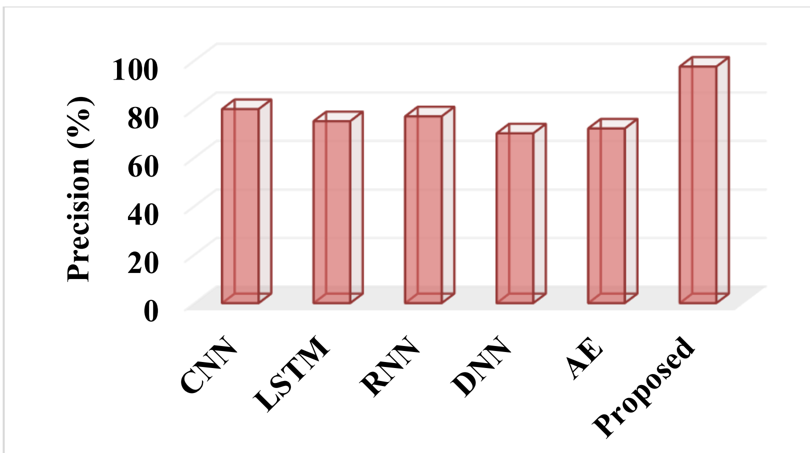

Fig. 4. Precision comparison

Figure 5 compares the recalls between different existing systems for disease prediction and the proposed system using RNN+CNN. Recall is otherwise called sensitivity or true positive rate and is the ratio of actual positives that the model has identified correctly. This is so crucial in a medical diagnosis, as if a model fails to identify a disease, the patient will be at great risk. It is in this context that the recalling values vary from a minimum of 70% to a maximum of 82%.

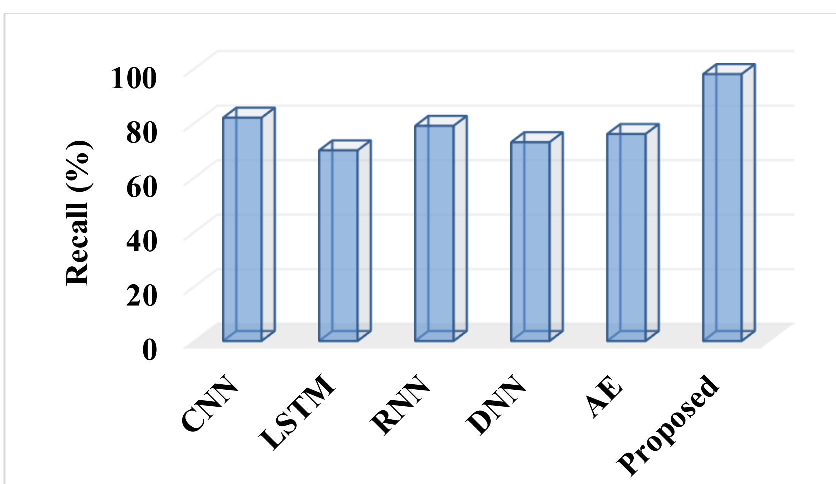

Fig. 5. Recall comparison

This gives a recall of 82%, which illustrates good performance regarding the identification of positive cases. The proposal model RNN+CNN outperforms this benchmark by a recall of 98%. This impressive increase points out that the model can efficiently avoid false negatives. It integrates RNN into the architecture, where the main ability for the capture of sequential dependencies in the data exists to a great extent-very important for disease identification that is developing with time. In this case, the CNN part increases feature detection for the systems to observe small signs of diseases in images or signals which would otherwise have been skipped. The sum of these factors will ensure that most of the actual cases of the disease are identified and the prospects for the patients will be much better; this is a result of the fact that earlier interventions are more likely to happen. Increased recall in the proposed system testifies to its superiority in recognizing diseases that would lead to its practical implementation in an actual healthcare setting.

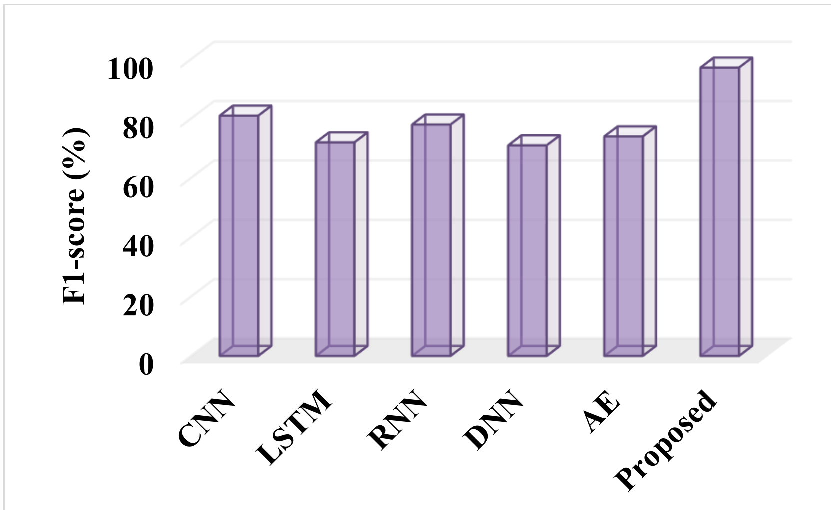

Fig. 6. F1-score comparison

Figure 6 gives the F1-score comparison for different systems of disease prediction. The F1-score is the harmonic mean of precision and recall. Hence, this measure is balanced, taking into consideration both false positives and false negatives. That will be more useful in the case of class imbalance, since this measure returns one number and also considers precision and recall. Whereas the F1-scores of the different existing systems range from 71% to 81%, in the proposed RNN+CNN, there is a considerable increase of 97%. This means that on top of being good both independently in precision and recall, the proposed system effectively balances both, an essential requirement toward effective disease prediction. This is possible because of the robust architecture the model RNN+CNN allows to learn from, complexities, and nuances in the data, hence giving improved predictions in both metrics. The higher F1-score suggests that this model is reliable enough for healthcare practitioners in terms of consistent performance; as such, it is of great value during diagnostics. In summary, the proposed system capabilities of increasing the F1-score show its efficacy towards enabling comprehensive understanding of the presence of diseases, something very helpful in making clinical decisions.

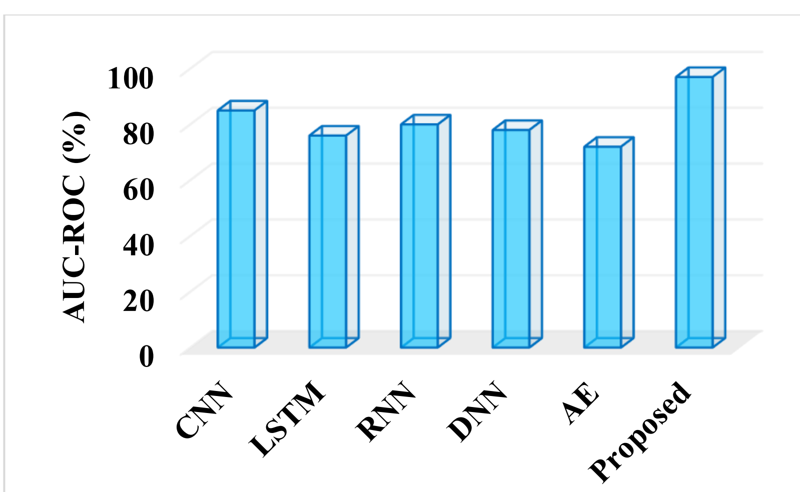

Fig. 7. AUC-ROC comparison

As shown in Figure 7, the AUC-ROC (Area under the Receiver Operating Characteristic Curve) comparison among existing systems and the proposed RNN+CNN-based model. AUC-ROC means the probability that a randomly selected positive instance will be ranked higher than that of a randomly chosen negative instance, and it is an important metric to compare binary classifiers. The AUC values of the current systems vary from 0.72 to 0.85, and the highest AUC is achieved by existing model, which demonstrates relatively good classification capability. On the other hand, the proposed RNN+CNN model outperforms its counterparts by a big margin at an AUC-ROC of 0.97. This indicates a strong increase in AUC, with the implication that the proposed system was much better at distinguishing between positive and negative cases over a wide range of thresholds. It contributes to this improvement, coming from the hybrid architecture that effectively combined the strength of RNNs and CNNs toward learning complex representations from time-series data along with images. The proposed model will therefore have more capability of discrimination by effectively utilizing temporal and spatial information, hence yielding better clinical outcomes. A higher value of the AUC-ROC shows the potential of the proposed system in real-world applications where the prediction of diseases is highly crucial for timely interventions.

As shown in Figure 8, inference time comparison among the different disease prediction systems is presented, which is the time a model takes in making predictions after training. This metric is very important clinically, since timely decisions may determine patient outcomes. The range of inference times among the systems is from 0.4 to 1.5 seconds. Existing model has a maximum time consumption of 1.5 seconds per prediction, while that of the proposed RNN+CNN is remarkably 0.4 seconds. This definitely stands as a decisive advantage, enabling healthcare experts to receive predictions almost in real time and thereby respond promptly to patient needs. This is largely reduced inference time as a result of optimized architecture of the combination RNN and CNN, which processes input data with efficiency and employs parallel computing. This is very important in emergency settings, as delay may have serious implications. The proposed system, therefore, can deliver faster predictions that enhance clinical workflow and make sure that timely and appropriate care for the patients is provided. Therefore, the comparison of the inference times does indeed point out the practicality that can be expected from the proposed RNN+CNN model, reinforcing its suitability for deployment in cloud-based healthcare environments where rapid access to information becomes critical.

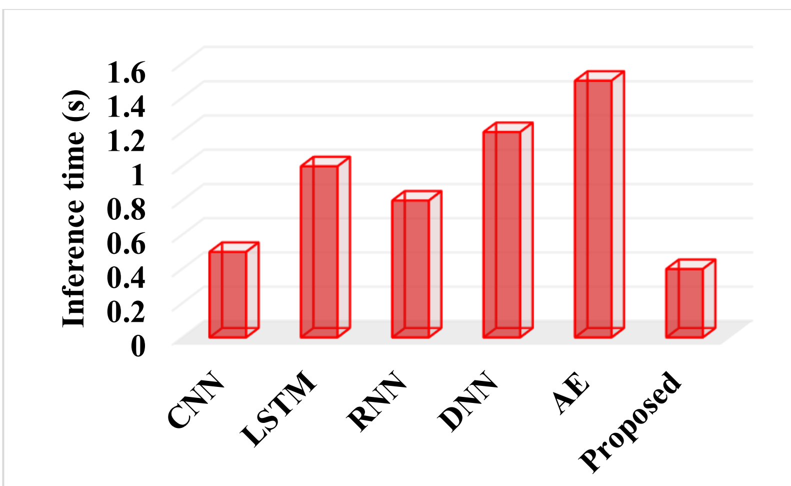

Fig. 8. Inference time comparison

5. CONCLUSION AND FUTURE WORK

This paper tends to develop a big data approach to designing a disease prediction system with cloud-based RNN+CNN. Since the model is developed by integrating the strengths of RNNs and CNNs, it very efficiently handles the challenges associated with disease prediction from various forms of data, image, and time-series in particular. The hybrid architecture proposed in this paper results in higher prediction accuracy, precision, recall, F1-score, and AUC-ROC performance metrics than those obtained by state-of-the-art systems, as it further enables improved feature extraction and temporal analysis. The experimental results prove that the proposed system outperformed the state-of-the-art models in almost all the evaluated performance metrics with a difference, hence showing its efficacy in identifying the correct cases for disease. The proposed model has an impressive inference time of only 0.4 seconds, further making it quite pragmatic for real-world applications in clinical practice, hence very helpful to healthcare professionals. While the RNN component captures the sequential dependencies in the data with the best insight possible, the CNN component extracts spatial features from image data with equal proficiency. This is really useful for a more holistic analysis of patient information. Also, scalability of the proposed system is emphasized, showing the potentiality of handling volumes of data in cloud environments-precisely what modern healthcare systems need, with the current trend toward big data analytics. Similarly, integrating cloud computing further enhances access and computational efficiency, therefore enabling health practitioners to take advantage of sophisticated predictive analytics, which, in turn, are unhindered by local processing limitations. This RNN+CNN-based disease prediction system is a very important advance in the medical information field. With the high performance of the proposed model, real-time processing capabilities, and scalability, it surely will help enhance diagnosis and improve outcomes for patients. Model refinement, further data modalities, and real-world validations will be pursued in future works in order to establish its efficacy for varied clinical scenarios.

Funding:

The authors did not receive any funding from public or private organizations to carry out this research. The study was undertaken with self-support and institutional facilitation.

Conflicts of Interest:

The authors declare no competing interests.

Acknowledgment:

The authors sincerely thank their institutions for their invaluable encouragement and logistical support in the completion of this research work.

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