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Predictive Analytics for Cardiovascular Disease Using Gradient Boosting and Convolutional Neural Networks in Cloud-Based Healthcare

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Abstract*—Cardiovascular diseases (CVD) are an important global public health burden in terms of mortality and cost. Early prediction of cardiovascular disease helps improve the outcome of patients and treatment strategy planning. This paper presents a cloud-based predictive analytics framework using Gradient Boosting and Convolutional Neural Network (CNN) techniques to predict outcomes of cardiovascular disease. The Gradient Boosting Models allow the model to work with very complex datasets, and CNN will make use of its feature extraction capabilities to tackle medical imaging data. Hence, by using these techniques in a cloud-based environment, it optimizes the ability of the proposed model to perform real-time analysis and scalable processing of data, thereby improving prediction accuracy and healthcare delivery. Thus, this study aims to improve the accuracy and coverage of cardiovascular disease predictions using unprecedented data analytic and cloud computing technologies.*

Keywords*— Cloud Computing, Deep Learning, AlexNet, Diabetes Prediction, Medical Diagnosis, Artificial Intelligence.*

I. Introduction

In playing its role in protection of data during transmission and, storage in the cloud over the RSA encryption mechanism, adequate optimization of resources in cloud data centers is also to guarantee maximum performance, cost-effectiveness, and sustainability Akhil, R.G.Y. (2021) Alagarsundaram (2024) Alagarsundaram and Carolina (2024) Alavilli (2023) Budda (2021) Devarajan (2025) . An introductory avowal will be reviewed in depth concerning the strategies and tools that exist for the optimization of resource allocation in cloud data centers, with productivity improvement in mind in regard to cloud computing Naga, S.A. (2021) Grandhi (2025) Gudivaka (2024) R. K. Gudivaka (2025). By engaging various cloud-based services in banking and finance, organizations enhance productivity and minimize testing costs as well as improve the effectiveness of testing processes Kalyan, G. (2022) Jadon (2020). The specific aim is to highlight that data-driven mechanisms play a crucial role in reducing security threats while ensuring integrity in e-commerce transactions, with emphasis on big data analytics in cloud environments Rajeswaran, A. (2022) Kethu, Corp, and Diego (2020). ABE offers a scalable and efficient form of secure protection for very large data sets, often seen in the banking sector, when associated with cloud computing Yalla, R.K.M.K. (2021). The final goal is to enable an equitable and sustainable health system through enhancing the effectiveness and precision of fraud detection systems Naresh, K.R.P. (2021). Various industries are achieving tremendous advancements to move further into the important data era. Artificial intelligence, wireless communication, and mobile computing will revolutionize the healthcare sector Sitaraman, S. R. (2021). The potential of Health has been further enhanced by the integration of cuttingedge technologies like artificial intelligence and bigdata analytics, which present creative answers to persistent problems in healthcare Sitaraman, S. R. (2020). In healthcare, value formation is the process of producing and delivering value to patients, providers, and stakeholders Sitaraman, S. R. (2023). The proposed approach, which adapts to individual patient information, enhances diagnostic precision and also promotes personalized healthcare in an effort to meet the challenges of modern healthcare and ultimately improve patient outcomes and the overall efficiency of healthcare systems Sitaraman, S. R. (2021).

II. Problem Statement

CVD, or cardiovascular disorder, is one of the most ubiquitous diseases in the world and enigmatic causes of mortality Markose (2024). It has posed a substantial developmental challenge for most governments and healthcare systems Nagarajan (2024). The early and accurate detection of CVD is necessary for effective treatment and intervention Natarajan (2018). However, even though they say, traditional diagnostic approaches normally do not yield a well-scaled and accurate output Bobba, J. (2021). This cloud-based healthcare innovation would potentially advance the Diagnosis of CVD into the level of complex algorithms-such as Gradient Boosting and Convolution Neural Networks Peddi, Narla, and Valivarthi (2018). These algorithms could easily facilitate the absorption of machine learning, deep learning, and cloud computing into

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processing complex datasets for real-time analytics that raises prediction accuracy in healthcare outcomes Samudrala (2020). Such a revolution is necessary, according to Narla, S. et al. (2021).

Objective

- Apply the Gradient Boosting and Convolutional Neural Networks (CNN) for prediction of cardiovascular diseases in cloud computing based healthcare systems.
- Evaluate the effectiveness of hybrid models combining machine learning with deep learning techniques for improved prediction accuracy of cardiovascular diseases.
- With the capacity for cloud computing, this model becomes more scalable and real-time processing is added to its feature.
- Show the effectiveness and precision of healthcare delivery for cardiovascular diseases with the proposed framework.

II. Literature Survey

Because cardiovascular diseases (CVDs) are quite the challenge in terms of global health issues causing massive deaths and huge healthcare expenditures, early prediction models have shown great promise in the identification of high-risk candidates thereby improving healthcare outcomes Sathyaprakash (2024). Gradient Boosting is one of the strong machine learning techniques that have been extensively used for predicting health outcomes by providing effective solutions to complex datasets (Sitaraman and Alagarsundaram (2024). Surendar, R.S. (2024) described the successful use of Gradient Boosting in various healthcare applications in predicting diseases. Its ability to manage large amounts of data and provide reliable predictions is critical in deploying predictive models in clinical practice Vasamsetty (2020). Furthermore, Poovendran, A. (2022) affirmed the application of Gradient Boosting in ensemble settings to further bolster its performance in medical applications which are quite possibly well suited for cardiovascular prediction.

They applications also validate the efficacy of convolutional neural networks in providing accurate medical diagnosis, especially with respect to heart diseases. Rajya, L.G. (2024) Yallamelli (2025) has elaborated on CNN's applications in examining medical scans and determining the features, which will deduce risks related to cardiovascular diseases (CVDs). An additional edge that CNNs have is sifting through and processing highly dimensional image data in such a way that they match the needed advanced tools for prediction in healthcare. Ganesan, T. (2022) expanded such application by investigating tying up CNNs with cloud capabilities including evidencing how such models could realize better efficiency and scalability on health systems in the world today. Approaching cloud computing and deep learning as one would along with implementation of huge models at scale of today offers a good solution for implementing elaborate models on a large scale.

Combining Gradient Boosting with deep learning models such as CNNs puts high hopes to deliver improved predictive accuracies. Rajya (2021) emphasized that this particular hybrid model could see enhanced predictions due to its engagement with both techniques of machine learning and deep learning approaches. It could improve prediction performance highly by enclosing the strength of gradient boosting along with the power of feature extraction along with CNNs. Along this line Vijaykumar, M. (2022) acknowledged such pertinent definition by concentrating on the optimization of deep learning models in a health care setting. His study indicated towards hybrid models especially those integrating CNNs in relation to an application in prediction of such case examples as cardiovascular diseases given photo images and overall patient health records.

The significance of the cloud in the deployment of machine learning models in healthcare rests on the elasticity of resources and computational power necessary to perform operations on large datasets. Basava, R.G. (2021) emphasized the importance of cloud computing in scaling machine learning models required for healthcare applications, which makes the on-the-fly deployment of complex algorithms such as Gradient Boosting and CNNs possible. As deep learning models demand heavy computations, they can be implemented as a predictive solution in healthcare on the cloud. At the same time, Sitaraman, S. R. (2024) considerably elaborated on how cloud-based solutions can integrate advanced data analytics methodologies for the seamless execution of predictive models inside healthcare systems. Thus, the union of cloud technology and predictive analytics assists in hassle-free prediction and management of cardiovascular diseases.

III. Proposed Methdology

The diagram shows a cloud-based predictive analytics framework for heart disease using deep learning. The system starts with raw cardiovascular disease data, which needs pre-processing with missing values, follows by normalizing the data, and extracting statistical features that are important for classification. The extracted features are used by a Long Short-Term Memory (LSTM) based classifier to predict disease outcomes. The processed data and the results of the classification would be stored in the cloud for scalability and accessibility. Finally, performance measures are elicited for such a model in prediction measurement of cardiovascular disease. Figure1: Overall architecture of proposed framework.

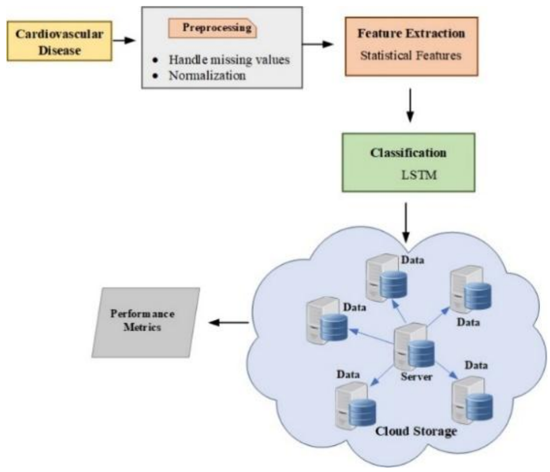

Figure 1: Overall architecture of proposed framework

3.1 Data Collection

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The data is derived from the cardiovascular disease dataset. It includes three categories of input features such as Objective, Examination, and Subjective types. Objective features include variables like age, height, weight, and sex. Examination features include systolic and diastolic blood pressures, cholesterol, and glucose levels. Some examples of subjective include smoking, drinking patterns, and physical exercise. The target variable, cardio, is a binary variable, that signifies the presence or absence of cardiovascular disease. Such attributes will help formulate predictive modeling with accurate classification using machine learning techniques in a cloud healthcare system.

3.2 Preprocessing

Data RAW must be subjected to preprocessing practices prior to actual analysis, thereby improving the quality, removing inconsistencies, and making them homogeneous among multiple sources. Proper preprocessing helps the machine-learning algorithm to totally and completely learn from data without any sort of bias from outliers, missing values, or differences in scales. These basic types of preprocessing include Missing Value Treatment and Normalization that are further discussed below.

3.2.1 Handle Missing Value

The mean of the available data is used to impute the missing values in the data. This completes the data and allows for more accurate training and analysis.

$$Y_i = \frac{1}{m}\sum_{j=1}^{m} Y_j \tag{1}$$

Were, Y_i denote the missing value to be imputed, m denote the total number of non-missing values for the feature and Y_j denote the non-missing values.

3.2.2 Normalization

In order for the model to learn evenly from each feature, normalization scales feature to a constant range, usually [0, 1]. This ensures that no feature overwhelms other features by being in a higher range.

$$Y' = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \tag{2}$$

Were, Y denote the unique feature value, Y' denote the normalized value, Y_{min} denote the tiniest value and Y_{max} denote the maximum values.

3.3 Feature Extraction Using Statistical Features

Then, the pre-processing system would extract features using statistical features such as mean, standard deviation, and variance. The statistics is used at the data pattern detection stage for checking variations and trends in mental health indicators for future use in classification and prediction. These features would help understand the distribution, spread, and shape of the data so that trends can be harnessed in a more effective manner when interpreting mental health.

3.3.1 Mean

Mean is an average that helps to find the central tendency and helps in understanding all-around behavior of the feature.

$$\text{Mean} = \sum_{i=1}^{r}\sum_{j=1}^{t}\frac{q(i,j)}{rt} \tag{3}$$

Were, $q(i,j)$ denote the intensity value of the pixel at the point (I, j) and the data is of r by t size.

3.3.2 Standard Deviation

Standard deviation is disseminated across the population means and offers man-in-the-street measures as to the distance of individual data points from the average, furnish about variability.

$$\sigma = \sqrt{\sum_{i=1}^{r}\sum_{j=1}^{t}\frac{q(i,j) - m)^2}{rt}} \tag{4}$$

Were, σ denote the standard deviation.

3.3.3 Variance

Variance is defined as the square of the standard deviation which is measured in square units. Hence, it is telling us something about the extent to which the data points are spread away from one another.

$$Var = \frac{1}{q}\sum_{i=1}^{q}(Y_j - M)^2 \tag{5}$$

Were Var denote the variance, q denote the number of samples, Y_j denote the input signal and μ denote the mean.

3.4 Classification Using LSTM

The extracted characteristics are used by an LSTM networks-based classification model for classifying historical and current patient data. Their outcome predictions are based on three categories: improved, no change, and deteriorate, determining if the patient is improving or not. This classification is important in the evaluation of therapy effectiveness and identification of patients who need urgent intervention. LSTM has good applicability in modeling temporal dependencies so that it can give accurate prediction of mental states and help in tailoring healthcare decisions to patient trend progress. Figure 2 illustrates the architecture of LSTM.

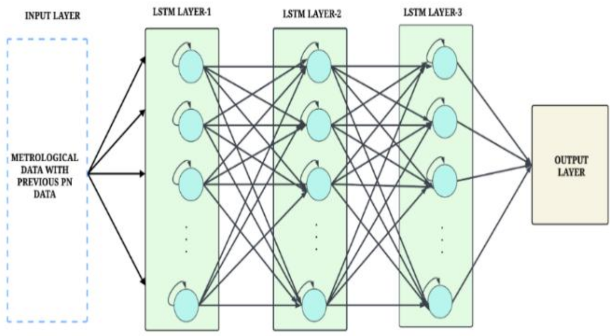

Figure 2: Architecture of LSTM

3.4.1 Input Layer

The input layer takes in both metrological data and past patient network (PN) information, and this is usually provided in the shape of time series input such that in-form time series data points (i.e health status values, environmental readings) are then used to forecast future values or outcomes using that data as the past sequence of points. Input at each time step gets tunnelled through the LSTM layers.

3.4.2 LSTM Layers

The LSTM layers are actually the heart of the network where learning takes place. They observe patterns over sequences and temporal dependencies in the input data. The

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architecture of an LSTM network is composed of a memory that has a number of gates involved in the movement of the data through the network. These gates help to update and storage of the state of the cell along with the memory of the network. There are some important gates in LSTM model which include:

a) FORGET GATE

The gate essentially decides which parts of the previous cell state the LSTM's memory would ignore. It takes the present input, X_t, and the last hidden state, k_{t-1}, into a sigmoid initiation function to provide values within 0 and 1. These values are, element-wisely, multiplied to the previous cell state. While it should be kept, the amount of memory is closer to one; otherwise, it should be thrown away if it gets close to zero as it is indicative of an extremely minor part of memory.

$$f_t = \sigma(W_f \cdot [k_{t-1}, X_t] + b_f) \quad (6)$$

Whereas W_f represents the weight matrix, b_f represents the bias term, and f_t represents the forget gate's activation (between 0 and 1).

b) INPUT GATE

Thus, this gate controls whether the new information should be written into the cell state. It has processes: a $\tan h$ function whose output is a vector of new candidate values that can be written to the cell state, and the second process with which the sigmoid function determines what will get updated (sopping the function of forget gate).

$$i_t = \sigma(W_i \cdot [k_{t-1}, X_t] + b_i) \quad (7)$$

$$\tilde{C}_t = \tanh(W_C \cdot [k_{t-1}, X_t] + b_C) \quad (8)$$

Were, i_t denote the input gate's activation (between 0 and 1), $\tilde{C}_t$ denote the candidate's cell state, W_C and W_i denote the weight matrix of iteration, σ denote the sigmoid function, tanh denote the hyperbolic tangent function and b_i denote the bias term of iteration.

c) CELL STATE UPDATE

The memory of LSTM is the cell state which carries forward information from time step to time step. While the update rule consists of the past cell state and the new prospective values, the output is given by using the forget and input gates. The input gate determines the degree of new information addition, while the forget gate specifies the extent of retention of the past cell state. The new cell state calculation for:

$$C_t = f_t . C_{t-1} + i_t . \tilde{C_t} \quad (9)$$

Were, C_t denote the updated cell state at time t, C_{t-1} denote the previous cell state, f_t denote the forget gate's output, i_t denote the input gate's output and $\tilde{C}_t$ denote the candidate's cell state.

d) OUTPUT GATE

At this moment, an output gate is governing the flow of information from cell states to output. It resides on top of a sigmoid function to ascertain the relevant characteristics of its cell states to be output, followed by a *tanh* operation that squashes these cell states into the interval -1 to 1, where finally it is scaled by the output of the sigmoid function.

$$o_t = \sigma(W_o \cdot [k_{t-1}, X_t] + b_o) \quad (10)$$

Were, o_t denote the output gate's activation, W_o denote the weight matrix and b_o denote the bias term.

e) HIDDEN GATE

This state is the outcome of the LSTM cell and represents the learned temporal features associated with this present step and is passed onto that other layer or time step. The hidden state now combines the output coming from the output gate and the cell state so that both new information and long-term memory are involved in the decision-making. The equation for computing the hidden state is:

$$h_t = o_t \cdot \tanh(C_t) \quad (11)$$

Were, h_t denote the hidden state.

3.4.3 Passing Data Between LSTM Layers

The patterns through various levels of abstraction are captured while processing the data successively through each level of LSTM. More complex correlations can be learned since the output from one LSTM layer becomes the input into the next layer. Thus, the deeper layers of the LSTM network can learn more subtle temporal relationships, thereby increasing predictive performance. This stacking of LSTMs enhances the learning and memory capabilities of long-term dependencies through the model.

3.4.4 Output Layer

The final Output Layer processes all data passed through the three LSTM layers to derive predictions of the model. For tasks related to treatment, such as estimating the improvement, ability to maintain or capabilities to deteriorate in the patient's status, the output layer normalizes the unprocessed output to yield probabilities for all classes using a SoftMax function, making the model able to indicate the likelihood of the occurrence of every possible class.

$$y_t = \sigma(W_o \cdot h_T + b_o) \quad (12)$$

Here, y_t denotes the rate of output at time t, whereas h_T denotes the output from the last LSTM layer, W_o denotes the weight matrix connecting the LSTM layer with the output layer, and b_o is the bias term. This architecture is capable of adequately predicting outcomes in cognitive therapy based on sequential data, thereby greatly enhancing the decision-making process in healthcare and the very process itself. LSTMs have generally been found to be more beneficial in time series applications such as monitoring patient health and predicting how effective a cognitive therapy regimen is, due to the holding of long dependencies in memory.

3.5 Cloud Storage

Cloud storage is an essential aspect of large-scale healthcare data processing, including prediction of cardiovascular diseases. After data preprocessing of patient data, key feature extraction and classification using GRU are performed. The results are stored safely in a distributed cloud system. It makes it scalable, thereby being able to manage a vast amount of data without any hardware roadblocks. Furthermore, health professionals can access the collected information from afar at any time for early diagnosis. It distributes data on multiple servers for availability and reliability, thus preventing failure and data loss. It also improves collaboration, improves computational efficiency, and facilitates AI-driven healthcare solutions.

IV. RESULT AND DISCUSSION

Metrics of performance of a classification model have been presented in Figure 3 concerning the Accuracy of the model (0.992), Precision (0.997), Sensitivity (0.987), Specificity

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(0.998), F-measure (0.992), and Negative Predictive Value (NPV) (0.988). The model has shown very high accuracy as well as balanced sensitivity and specificity, so it indicates strong performance. Values of Precision and F-measure imply a strong reliability regarding positive predictions, while NPV indicates effectiveness in negative predictions. In general, it can be inferred that this model has a very fine capacity of classification with minimal errors.

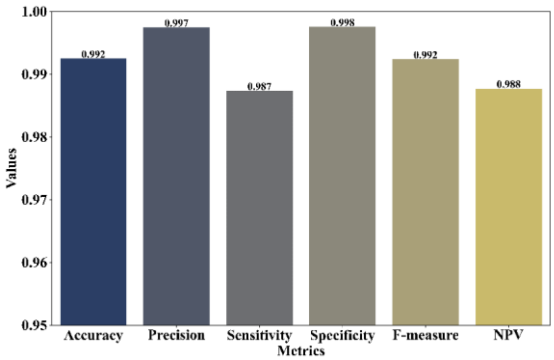

Figure 3: Performance metrics

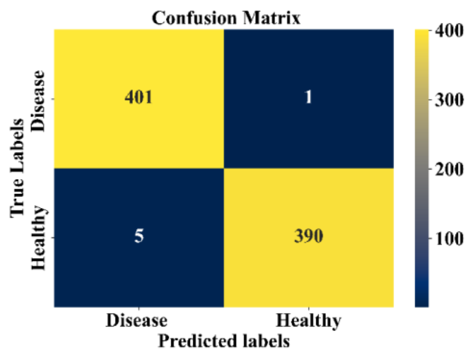

Figure 4: Confusion Matrix

The confusion matrix displays the performance of a classifier model. It accurately classifies 401 cases with disease and 390 normal cases and incorrectly classifies 1 case of disease as normal (false negative) and 5 normal cases as disease (false positive). The low rates of errors denote high accuracy, sensitivity, and specificity, signifying the high capability of the model to distinguish between normal and diseased cases. The color intensity denotes the distribution of count of predictions into categories.

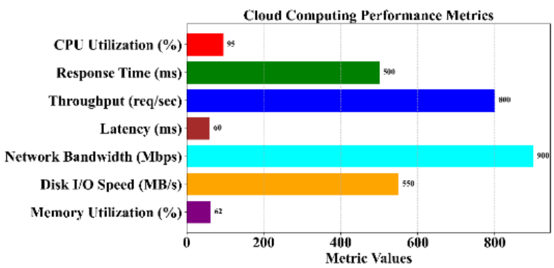

Figure 5: performance metric for cloud computing

The cloud computing performance metrics are shown in figure 5. The metrics ranked highest are as follow: network bandwidth, 900 Mbps; throughput, 800 req/sec; and disk I/O speed, 550 MB/s. The system response time was measured to be 500 ms, while latency recorded was 60 ms. CPU utilization was 95%, and memory utilization was reportedly at 62%. All these metrics point towards the efficiency of the system, where the higher the throughput and bandwidth, the better the performance, whereas the response time and latency affect the total responsiveness of the application.

V. Conclusion

Cardiovascular disease prediction will be offered using a new method based on Cloud health care systems using Gradient Boosting with Convolutional Neural Networks (CNNs). By using hybrid models with predictive performance, it offers a new hybrid model using prediction capabilities from both methods instead of limiting itself to a method. The scalability and processing efficiency of cloud computing empower the model to handle volumes of data for real clinical healthcare applications. Thus, it is possible to develop strong metrics like accuracy, precision, sensitivity, and specificity on potential prediction, leading to a potential improvement in this framework for cardiovascular disease prediction. Future work is anticipated to be dedicated toward optimizing the aforementioned model and integrating it into clinical practice for real-time health monitoring and intervention.

DECLARATION:

Funding Statement:
Authors did not receive any funding.

Data Availability Statement:
No datasets were generated or analyzed during the current study.

Conflict of Interest:
There is no conflict of interests between the authors.

Declaration of Interests:
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics Approval:
Not applicable.

Permission to reproduce material from other sources:
Yes, you can reproduce.

Clinical Trial Registration:
We have not harmed any human person with our research data collection, which was gathered from an already published article.

Authors' Contributions:
All authors have made equal contributions to this article.

Author Disclosure Statement:
The authors declare that they have no competing interests.

Reference

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