Deep Learning-Driven Novel Strategy For Iot-Cloud-Based Smart Healthcare Monitoring System

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Internet of Things (IoT)-enabled mobile healthcare apps provide millions of people with web-based amenities and health assistance. Massive quantities of big data are handled by such applications, which also make utilization of cloud computing (CC) for open and secure preservation. In the rapidly evolving field of healthcare used for better well-being and way of life, CC is vital. This work suggested IoT-cloud-driven healthcare system for tracking and recognizing critical illnesses to provide consumers with better services than digital medical applications. This paper introduces a novel quality-aware feature-tuned deep belief network (QF-DBN)for diabetes illness diagnosis and severity assessment. The generation of disease knowledge from healthcare information presents challenges for conventional DBN. QF-DBN combines health-related variables, develops effective Restricted Boltzmann Machine (RBMs), and trains RBMs to discover deep disease-relevant characteristics. In the first stage, medical data is created by utilizing medical sensors and open-source datasets to identify individuals who are likely to have severe diabetes. For enhancing the data by removing noisy data, min-max normalization is used in the second stage of data preprocessing. The third stage involves determining the set of features through the use of linear discriminant analysis (LDA). The proposed QF-DBN framework predicts diabetic illness in the fourth stage. In the fifth stage, the effectiveness of the suggested model is examined; along with a comparison between the suggested and current models. The research utilized SPSS and t-test for statistical analysis. The results of the experiment show that in a smart health surveillance system, the QF-DBN strategy performed better than other approaches.

Keywords- Smart healthcare, IoT, cloud computing (CC), diabetes, severity prediction, quality-aware feature-tuned deep belief network (QF-DBN)

I. INTRODUCTION

Diabetes is a condition that impacts how blood sugar is metabolized, 537 million people globally had the illness in 2021 and that statistic is predicted to rise to 643 million by 2030. India is among the nations with the greatest rates of insulin resistance, with over 77 million documented cases. This indicates an especially high prevalence [1]. This emphasizes how urgently efficient detection and management techniques are needed. Standard glucose levels tests, such as hemoglobin A1c (HbA1c), oral tolerance to glucose tests, and fasting sugar tests, are used to detect diabetes. New developments present non-invasive tools that provide real-time glucose information [2]. Diabetes detection technology is more accurate and predictive when AI and machine learning are combined network to correctly track and deal with scientific disorders. It monitors blood glucose levels, food, workout, and solution compliance inside the treatment of diabetes [3].

Smartphones with sensors and smart glucose meters are examples of Internet of Things gadgets that collect information for evaluation and offer insights and tailor-made recommendations. By being proactive, this method allows to improve patient consequences and reduce headaches. Neural networks are a form of AI known as deep learning to know that use massive quantities of statistics to analyze [4]. It evaluates complex datasets inside the scientific area to forecast the course of disease. Accurate diagnosis and individualized treatment tactics are advantages of dealing with diabetes. Computing assets and records necessities are demanding situations. Information from IoT devices is processed and managed via the IoT cloud, particularly inside the healthcare enterprise [5]. Health facts is accumulated, stored, and analyzed by it to enable instantaneous assessment and tracking at a distance.

Optimizing care for sufferers and operational efficiency are two benefits of integrating with clinical statistics which can be electronic [6]. A machine learning algorithm that includes several layers of latent variables, such as a deep belief network (DBN) is perfect for uncontrolled applications like extracting features. DBNs presents statistical analysis and custom designed clinical solutions in the healthcare enterprise via analyzing patient information to discover styles and assist with sickness diagnosis [7,8]. The accuracy of disease detection is improved using a quality-aware feature-tuned deep belief network (QF-DBN), which uses quality measures to choose pertinent features. In order to provide strong and trustworthy clinical decision support for the diagnosis of diabetes, it examines patient data to find important signs and evaluate severity. Figure 1 represent the Healthcare monitoring systems.

Fig.1. Healthcare monitoring systems

A. Contribution of the paper

- This research monitoring the IoT-Cloud-based smart healthcare system and provides a novel QF-DBN for diabetes illness diagnosis.
- For enhancing the data by removing noisy data, min-max normalization is used in the second stage of data preprocessing.

- The third stage involves determining the set of features through the use of linear discriminant analysis (LDA).
- When compared to other existing methods, our proposed QF-DBN method achieves a better outcome.
- The proposed Quality-Aware Feature-Tuned Deep Belief Network (QF-DBN) addresses the shortage of focus on environmental sustainability with the incorporating quality metrics into healthcare systems. It complements security and scalability through integrating function customization and high-quality consciousness, ensuring secure control of sensitive healthcare facts.
- Additionally, QF-DBN optimizes facts analytics to enhance patient outcomes, providing a complete approach to the demanding situations confronted in IoT-based totally smart healthcare systems.

B. Organization of the paper

The rest of the paper is as follows: Related works are included in part 2. Part 3 included thorough a methodology. Part 4 presents an analysis of the findings, and part 5 provides a conclusion.

II. RELATED WORKS

A. Data driven techniques used in diabetes

Study [9] created a data-driven decision algorithm to determine how best to allocate preventative treatments to patients who are at risk at a reasonable cost. To be more precise, they integrate algorithms for machine learning, optimizing, and causal inference methods to create a scalable decision model. Because the decision model was generic, it can be used to other preventable illnesses in order to effectively allocate preventive care. Study [10] employed two diabetes cohorts to create five subgroups using k-means clustering. As development indicators, they also made a direct comparison between the k-means discrete subgroups and clustering characteristics. Assessment was done on cluster integrity over follow-up. Instead of being the foundation for reducing grouping indications, data-driven subgroups work better as a compliment. Study [11] used data mining approaches to present a type 2 diabetes predicting model. Python is used to train the suggested method, and an actual dataset gathered from Kaggle was used for analysis. In addition, the matrix of confusion, sensibility, and accuracy metrics for performance are used to analyze the effectiveness of the suggested mechanism. Study [12] presented the development of an autonomous diabetic prediction system employing different machine learning algorithms and an exclusive dataset of female patients. Following training and testing on every categorization model, the suggested system yielded the best outcome. Moreover, the domain adaption approach has been used to show off the suggested system's adaptability. Study [13] used data-driven machine learning techniques to take use of cutting-edge deep learning models develop on convolutional neural networks (CNN). The research delves into the difficulties associated with automated disease diagnosis in healthcare images with CNNs. These problems involve pre-processing methods, performance measures for unbalanced classes, as well as training on accessible databases.

Study [14] classified the retrieved characteristics of the diabetic retinal degeneration dataset using a deep neural network model based on the analysis of principal components and the Grey Wolf Optimization (GWO) method. The findings demonstrate that when compared to the previously discussed methods, the suggested model performs better. Data mining techniques, such as predict and model-based classification, evaluate many aspects regarding diabetes data and retrieve significant data for early detection and estimation of the condition were used in [15]. Involving diabetes being a rapidly developing chronic illness with serious health risks, statistical and algorithms for prediction may greatly enhance the detection and treatment of the condition. The Random Forest (RF) approach will be used to examine and contrast the data from the Public Investments Management Assessments (PIMA) Indians and Abelvikas datasets [16]. On the two datasets, highly different outcomes were found according to the test results. Because more comprehensive sugar features support the Abelvikas dataset's characteristics indicates the dataset's characteristics were significantly superior. Study [17] focused on the publicly accessible diabetes dataset, they suggest four classifier models: Support Vector Machine (SVM), decision tree (DT), and Extreme Gradient Boosting (XGB) and K-nearest Neighbor (KNN). The models demonstrated excellent precision in identifying patients with diabetes, however, the XGB model had a marginal advantage over the other models. Considering the stakes involved in the medical industry, the designed interface can be improved even more by adding more comprehensive clinical data, which ultimately help medical professionals make better decisions. A refined random forest algorithm with optimal parameters (RFWBP), which was utilized in conjunction with feature design and the RF algorithm to identify diabetes patients early was introduced in article [18]. Several processing approaches were utilized to handle raw data during the preparatory stage. Subsequently, they employed further data mining techniques to augment the original dataset with relevant attributes. The findings of the experiment verify that the suggested RFWBP worked better than traditional machine learning techniques. A comparative comparison of the effectiveness of artificial intelligence techniques for classification was conducted in study [19]. Adjusting the classifiers' hyper parameters and using various information preprocessing approaches improves the classifier's performance. Four models have been developed for the experimental research, and each model was based on a dataset that was collected using various PIMA dataset preparation techniques. The KNN, DT, RF, and SVM classification methods have been applied to each model, and all the hyperparameters of the classifier have been adjusted to improve the model's performance. Study [20] employed a dataset of 520 cases, which was gathered by asked patients directly for questionnaires. After using tenfold cross-validation and proportional assessment approaches, they determined that RF had the best reliability on that dataset out of the three algorithms they used to examine that: Naive Bayes, Logistic Regression (LR), and RF. Lastly, a widely available, user-friendly tool has been suggested that allows the end user to determine their risk of developing diabetes by evaluating their symptoms and providing helpful advice on how to manage the associated risks. Data mining classification techniques to construct a diabetic prediction model was presented in article [21]. The difficulty of classifying data that was imbalanced, particularly in the field of medical information technology, served as the impetus for creating a classifier that employed the rebalancing method. The most effective classifier for an evenly distributed set to predict diabetes was chosen by consuming it to five classifiers: DT, SVM, MLP (Multi-Layer Perceptron), Simple Logistic, and Bagging. It involved preliminary processing the data used the Synthetic Minority

Oversampling Technique (SMOTE). A 10-fold cross-validation using an experiment on the medical documentation of 734 patients was used to achieve verification.
Article [22] developed an algorithm for predicting abstaining from blood sugar status using data mining and artificial intelligence, because management of diabetes and early detection might enhance outcomes and quality of life. To choose the most crucial features, the values of shapely were computed. To assess the resilience of feature significance, a noise assessment was carried out by incorporating Gaussian fluctuations into the numerical features. An artificial neural network, XGBoost, CatBoost, RF, LR, and other machine learning methods were employed to model the dataset. The key diabetes risk factors were correctly identified by a gradient boosted DT algorithm.

B. Deep belief network (DBN) and Quality Aware DBN

A Tabu Searching Optimization (TSO) method based on DBN called TSO-DBN was introduced in [23]. TSO-DBN has proven to be exceptionally effective in a number of medical domains. To enhance the results, two issues were addressed during the procedure. Considering its superior accuracy, the TSO-DBN model outperformed previous models in terms of performance. Study [24] suggested a mayfly optimization algorithm (MOA) developed with DBN and continuous brain Magnetic resonance imaging (MRI) characteristics for determining the classification of those with dementia into Alzheimer's Disease (AD) and non-AD categories. The experimental findings of the research show that the DBN-MOA algorithm, which was created with AD diagnosis in mind, was effective, superior, and applicable. Study [25] used a DBN with Rectified Linear Unit (ReLU) activation mechanism for predicting diabetes. Employing the minimal contrasting divergent method for the unsupervised path and the method of back-propagation for the supervised path, variables can be learned from the data. The outcome demonstrates that a greater level of diabetes prediction precision is offered by the DBN with ReLU activation capability. Study [26] suggested that the DBN approach incorporate the concept of an integrative algorithm, gather information from hospitals and analyze it into relevant elements, clean and process the information, and test and analyze the results of the processing again. According to the investigation's findings, an individual DBN classification outperforms logistical regression and support vector machines.
Study [27] suggested approval of the ensembles selection of features and DBN-based deep unsupervised artificial intelligence model for the early diagnosis of diabetes. The model was compared to alternative models that were lacking multiple layers that were hidden. According to the findings, DBN was a helpful instrument for the unsupervised early diagnosis of Type II diabetes. In order to establish a medical system that can classify and predict the onset of diabetic complications (Type 2) deep learning was used in [28]. The DBN was used to anticipate the negative effects associated with diabetes mellitus. It includes the classifying strategies of predicting diabetes, data collection and initial training. When compared to alternative machine learning approaches, the proposed approach yields more accurate results. The a two-dimensional DBN proposed in [29] was based on a Mixed-restricted Bayesian Machines and might accept numerous multifaceted inputs. The suggested deep neural network gathers the essential information to calculate the degree to which diabetic retinal degeneration is progressing. Experiments demonstrated the superiority of the suggested method over alternative approaches. The Taylor-primarily based DBN (T-based DBN) classifier was

proposed in [30] as a dependable and cost-effective technique to identifying damage and characteristics in the retinal cornea images. Based at the numerous layers related with diabetic retinopathy (DR), the recommended T-primarily based DBN changed into quite good at categorizing DR. Higher hypothetical error boundaries and a reliable detection charge are received by means of the counseled T-based DBN.

Study [31] presented an efficient deep belief network (DBN)-based intelligent distributed illness diagnostic model for the Internet of Things and the cloud. The medical data was mostly obtained via the DBN model that was being supplied from many sources. The collected data was then transferred to the cloud for additional processing. The cloud-based DBN model was utilized to classify patient data according to the existence of disorders. Diabetes and heart disease were the two medical datasets used to analyze the DBN model's results. The experimental findings confirmed that the DBN model changed into better than contemporary strategies through providing a maximum on the testing for diabetes, respectively.

A novel approach for diabetes threat assessment by using artificial intelligence methods were created in article [32]. Utilizing grouping and predictive methods of learning, the technique became built. The method makes use of a combination of DBN classifier for diabetes mellitus forecasting, an independent map for statistics aggregation. The effectiveness of the counseled method was contrasted with in advance method getting to know-advanced prediction structures. The results show that, for a choice of actual-international datasets, the applied strategy changed into able to nicely predicting diabetes mellitus.

The approach considers optical coherence tomography (OCT) photographs in order to efficaciously classify the DME manner [33]. The layer splitting step of the categorization method includes splitting up twelve layers and 13 boundaries. Additionally, the DBN category become used to categorize the OCT photographs as either ordinary or DME-affected. The Chicken Swarm algorithm was used to train the classification system, increasing identification performance. In the regard, the new technique performs better than other DME approaches currently in usage.

Study [34] proposed a Deep Learning (DL)-based model for anticipating Type 2 Diabetes Mellitus problems. For the purpose of forecasting complications of diabetes, the suggested model goes through the following stages: gathering data, preparation, extraction of features, DBN, verification procedure, and categorization. Finally, a comparison was made between the accuracy, precision, and recall of the existing methods and the suggested DL-based bMassive healthcare statistical analysis model employing DBN. The accurate management of diabetes greatly benefit from the application of the realistic prediction model.

C. Problem statement

The traditional method have the challenge of ensuring high-quality, consistent, and properly-included records across healthcare studies persists, hindering the generalizability and effectiveness of evolved models. The dependability of results is impacted by data variability, variation, and inconsistency in contemporary studies. Innovative strategies that concentrate an emphasis on data quality assurance, the smooth integration of various datasets, and the efficient use of analytics for better patient outcomes are desperately needed to overcome that. This study seeks to address these demanding situations by using growing a unique framework that enhances information pleasant, facilitates strong information integration, and maximizes the effectiveness of data-pushed healthcare solution.

III. METHODOLOGY

Wearable and implantable devices are included in the IoT. Medical data from faraway locations is gathered using these devices. When medical data is gathered via IoT devices connected to the human body, direct measurement can be obtained. The suggested methodology's flow is shown in Figure. 2. The healthcare diabetes data was first collected for study and the dataset followed preprocessing using the Min-max normalization method. Next, we use LDA for Healthcare feature selection. The suggested QF-DBN was utilized in the study to categorize healthcare monitoring systems

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Fig.2. Block diagram of proposed method

A. Dataset

We used a diabetic's data from (https://www.kaggle.com/datasets/mathchi/diabetes-data-set)Using wearable IoT devices that rely on sensors, this phase is in charge of gathering each patient's unique information. These wearable gadgets are affixed to the human body to continually and appropriately gather medical data or information about a specific patient. The goal is to determine a patient's probability of having diabetes based on diagnostic criteria. These samples were selected under certain constraints from a larger database. More specifically, Pima Indian women who are at least 21 years old make up every patient at this clinic. Additionally, the medical records kept at the hospital are utilized to map with the real data that is generated for each particular patient.

- **Age:** Years of (Age)
- **Pregnancies:** Number of pregnancies
- **Diabetes Pedigree Function:** diabetes in a family tree
- **Skin Thickness:** Skin-fold thickness (mm) of the triceps
- **Insulin:** Serum insulin after two hours (weight in kg/(height in m)^2)
- **Blood Pressure:** Blood pressure diastolic (mm Hg)
- **Glucose:** In an oral glucose tolerance test, the plasma glucose concentration after two hours

- **Outcome:** Class variable (o or 1)

B. Pre-processing using min-max normalization

After collecting the data, we preprocess the data using min-max normalization. The number of characteristics in diabetes, digestive and Kidney Diseases datasetC^{gc}, together with the diversity of their numerical values, make computing more challenging. Thus, normalization techniques are utilized to normalize data because of the mathematical difficulty of the computer process employed for healthcare predictionC^{ge}within the range of 0 to 1. There are several methods available for data normalization. The recommended approach uses the commonly used min-max normalization technique. This method translates an integer number, CU, of the source information using Equation 1 to compute C^{gc}intoCU_{norm}within the interval [0, 1].

$$\frac{C^{gc} - CU_{norm}}{CU_{max} - CU_{min}} \times [new\_max - new\_min] + new\_min \quad (1)$$

In this case, the transformed dataset's range is shown by $new\_min\, and\, new\_max$, whileCU_{norm}, C^{ge}, CU_{min}, , and $CU_{max}$are the values of the normalized information, the initial data, the original data, the most significant data and the lowest data respectively, throughout the whole dataset. $new_{min} = 0\, andnew\_max = 1$ are both used. All of the attributes' values fall inside the range when employing this technique [0, 1]. The optimal data preparation is ensured during pre-processing for IoT-Cloud-based Smart Healthcare Monitoring Systems using min-max normalization. This method enhances the predictive capacities of the system for efficient healthcare monitoring and management by uniformly scaling data characteristics from 0 to 1. By using this preprocessing, we effectively normalize and removing noise from the diabetics' patients' data. Figure 3 displays the block diagram for min-max normalization.

Fig.3. Block diagram for min-max normalization

C. Feature extraction using linear discriminant analysis (LDA)

Following preprocessing, LDA was used to select to choose relevant audio information and the IoT-cloud-based smart healthcare monitoring system's feature extraction process uses LDA to transform input data into a lower-dimensional space while preserving class distinction. The most discriminative characteristics for precise health monitoring are found by LDA, which also maximizes resource use and boosts system effectiveness. The fundamental supervised learning techniques use LDA to show the linear feature for maximizing the data separation between classes and reducing the data inside classes. The algorithm's formula can be expressed as the number of n, which represents the clusters of stock market regimes like the bull, sideways, and bear markets.

Let $\mu_j$be the sample mean, and let $\mu_j andM_j$ be the average and the total amount of data in the class ith, correspondingly. After that, the $T_X$can be stated as follows since ε_j stands for the scatter plot of the observations.

$T_x = \sum_{j=1}^{m} \Sigma_j$(2)

When the between-class scatter matrix,T_A, solution is given as:

$$T_A = \sum_{j=1}^{m} M_j \left(\mu_j - \mu\right)\left(\mu_j - \mu\right)^S \quad (3)$$

Eigen-values and eigenvectors are solved with the constraint that $T_X^{-1}T_m$.

LDA is used in the IoT-cloud-based smart healthcare monitoring system to extract features. LDA improves classification accuracy by effectively identifying discriminative characteristics from healthcare data. Real-time monitoring and analysis enable tailored healthcare treatments, improving patient outcomes by utilizing IoT sensors and cloud computing. Following feature extraction, QF-DBN was used to monitor smart healthcare based on IoT. Figure 4 represents the block diagram for LDA.

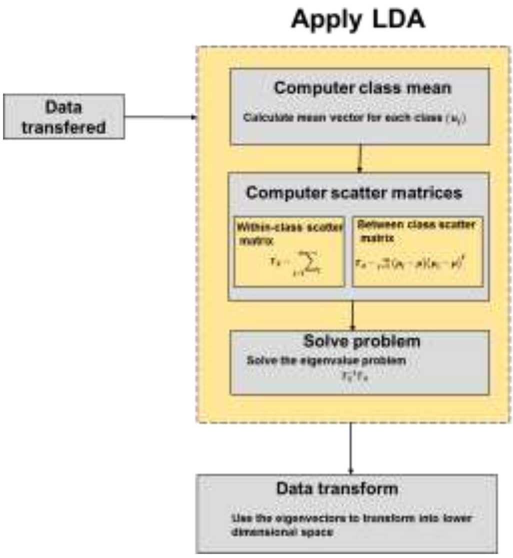

Fig.4. Block diagram for LDA

D. Smart Healthcare Monitoring System Based On Quality-Aware Feature-Tuned Deep Belief Network (QF-DBN)

Quality-aware feature-tuned deep belief network (QF-DBN) method incorporates deep learning into the monitoring of healthcare, ensuring feature optimization and quality-driven data analysis, enabling accurate insights and effective management in IoT-cloud contexts. Using hierarchical stacking, the fundamental SRBM modules can be combined to create a quality-aware feature-tuned deep belief network (QF-DBN). Figure 5 displays an exemplary structure of QF-DBN. Multiple RBMs and an extra output layer make up QF-DBN. Assume that QF-DBN has a total of TSRBM modules. The symbol for the sth SRBM is SRBM []. In this case, the words are identified about the sth SRBM using a subscript. Pre-training and fine-tuning phases make up QF-DBN training. This innovative method of delivering healthcare in the digital era enhances patient outcomes and makes the most use of available resources. It is an IoT-cloud-based intelligent medical surveillance system driven by DBN. The IoT-Cloud-based smart healthcare monitoring system uses QF-DBN to ensure accurate health assessments by analyzing data in real time. Through the provision of quick therapies, remote patient monitoring and efficient resource allocation, it enhances both the effectiveness of healthcare delivery and the results for patients.

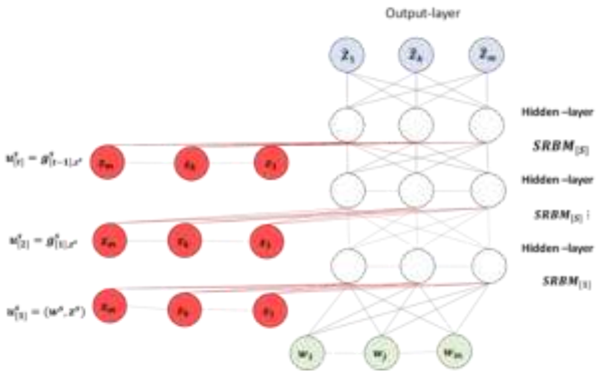

Fig.5. QF-DBN's intricate structure

❖ Pre-training

Initially, the visible state is created by combining the initial data along with the quality factor $u_{[1]}^{S} = (w^s, z^s), s = 1,2, \dots, S$to act as the first SRBM's $(SRBM_{[1]})$input.$(SRBM_{[t]})$Can be trained by applying an iterative gradient descent approach based on back-propagation (BP) utilizing the training data$\{(w^1, z^1), \dots, (w^s, z^s)\}$N Additionally, the state of the first-layer concealed feature can be accessed as $\{g_{[1]}^1, g_{[1]}^2, \dots, g_{[1]}^S\}$through the training data's forward propagation. Next, the first-layer data of hidden features $g_{[1]}^s,\ s = 1,2, \dots, S$is additionally mixed with the superior data $z^s, s = 1,2, \dots, S$ to function as the apparent input $u_{|2|}^s = (g_{[1]}^s, z^s), s = 1,2, \dots, S$ for the second-layer feature data to be learned by the second $(SRBM_{[2]})u_{|2|}^s,\ s = 1,2, \dots, S$.In a similar manner, $(SRBM_{[2]})$is trained using the BP method using the fresh training set.Similar to this, the T^{th}thlayer feature data can be acquired as $(SRBM_{[5]})$pre-trained$\{(g_{[1]}^1, z^1), \dots, (g_{[1]}^S, z^S)\}$.Then $\{g_{[t]}^1, g_{[t]}^2, \dots, g_{[t]}^S\}$will be mixed with the high-quality information$g_{[t]}^1, s = 1,2, \dots, s$asthe new input$z^s, s = 1,2, \dots, S$to acquire pre-training knowledge of higher-layer characteristics. This process is repeated until the final SRBM $(SRBM_{[t+1]})$ has been pre-trained using its training set $u_{[t+1]}^s = (g_{[t]}^t, z^t), s = 1,2, \dots, S$ It is evident from the above process that the pre-training

$\{(g_{[t-1]}^{1}, z^{1}), \ldots, (g_{[t-1]}^{S}, z^{S})\}$of QF-DBNprecedes in a layer-by-layer greedy fashion, starting at $(SRBM_{[1]})$and ending at$(SRBM_{[t]})$. As a result, process data can acquire deep hierarchical characteristics. Furthermore, because each SRBM input layer receives an extra addition of the quality variable vector in a stacked manner, QF-DBN can maintain the deep features primarily quality-relevant.

❖ Fine-tuning

As indicated by the blue circles in Figure 5, after pre-training, a layer of output is placed on the top hidden layer to predict quality. During the subsequent fine-tuning process QF-DBN can discover the right beginning weights for quicker and better modeling of the pre-training. When adjusting the QF-DBN network, the weighted and biased variables from the source through the last concealed layer are first applied to the network's characteristics that were obtained during the pre-training phase. Among the last hidden layer and output layer, the parameters are also initialized at random. Next, the anticipated quality variable is calculated at the output layer as,

$$\widehat{z}^{S} = affine(x_{[p]} g_{[t]}^{s} + a_{p}) \quad (4)$$

Where, the output layer's activation function is expressed as affine(•). The numbers indicate from the last concealed layer to the output layer, the connection weight and bias.$x_{[p]}$and a_p.For sample s, the expected output value is$\widehat{z}^{S}$. To optimize the QF-DBN network, the RMSE index is calculated for the training set.

$$RMSE_{sq} = \sqrt{\sum_{s=1}^{S} \|z^{S} - \hat{z}^{S}\|^{2} / s_{sq}} (5)$$

Here,s_{sq} is the training dataset's total number of sample.
The BP process is used to adjust the network's overall parameters until a set of convergence requirements are satisfied, after the computation of the network's RMSE.

❖ Testing

Following its offline training, QF-DBN can be applied to online testing sample calculation. The raw input data portion for the L^{th}sample during testing can be identified as $w^{S_{sq}+L}$. To perform forward propagation for output prediction, QF-DBN network inputs must include both the unprocessed data and the component of quality. In contrast to the training phase, wherein the training samples' quality variable information is pre-available, the quality variables for the testing samples are not known and need to be anticipated. Because of this, it is necessary to initially approximate the characteristics of quality for every test sample. Some basic models, like PCR, can be used to provide an approximate estimate. Because process industries are temporally correlated, it approximates the current testing sample using the quality data from the preceding instant. Stated otherwise, it begins with estimate on$z^{S_{sq}+L-1}$regarding the L^{th}testing specimen as$\hat{z}_{initial}^{S_{sq}+L} = z^{S_{sq}+L-1}$. Keeping in mind that whenever$z^{S_{sq}+L-1}$is not provided, the anticipated output of the QF-DBN of the $L-1$sample can be used to estimate the starting guess for the L^{th} testing sample as$\hat{z}_{initial}^{S_{sq}+L} = \hat{z}^{S_{sq}+L-1}$ .By combining the raw input variables with the preliminary estimation of the quality variable component, the visible input data for QF-DBN in quality prediction is produced. For the L^{th} testing sample, the visible input data is indicated as$u^{S_{sq}+L} = (w^{S_{sq}+L}, \hat{z}_{initial}^{S_{sq}+L})$. Lastly, by switching out $u^{S_{sq}+L}$ the final expected quality value, after input into the trained QF-DBN model, is determined as$\hat{z}^{S_{sq}+L}$ by forward propagation from the first layer to the last within the QF-DBN.

The primary operations of the QF-DBN-based soft sensor are displayed in Figure 6. Following the completion of the prediction for the testing dataset, the RMSE is determined as:

$$RMSE_{sf} = \sqrt{\sum_{l=1}^{S_{sf}} \left\| z^{S_{sq}+l} - \hat{z}^{S_{sq}+l} \right\|^2 / s_{sf}} \qquad (6)$$

Where s_{sf} denotes the test dataset's total sample count.

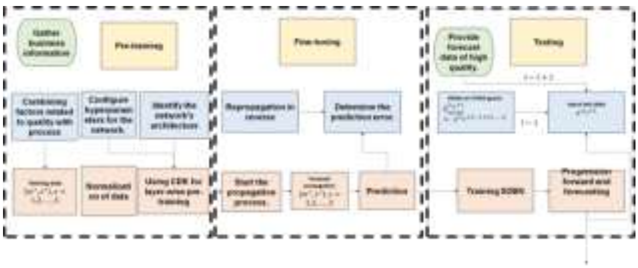

Fig.6. The suggested QF-DBN-based soft sensor model

By guaranteeing accurate data analysis and optimum feature extraction, the QF-DBN strengthens IoT-based healthcare monitoring systems and improves their capacity to identify abnormalities, forecast patient states, and enable prompt treatments. Its quality-conscious methodology improves dependability and guarantees precise insights for better patient care and health management instantly. Algorithm 1 represent the QF-DBN algorithm.

Algorithm 1: QF-DBN algorithm

Step 1: **import numpy as np**

Step 2: **class QF_DBN**:

```
def __init__(self, num_layers, num_features):
  self.num_layers = num_layers
  self.num_features = num_features
  self.rbm_layers = [RBM() for _ in range(num_layers)]
  self.output_layer = OutputLayer(num_features)
def pre_train(self, data):
  for i in range(self.num_layers):
    visible_data = data if i == 0 else hidden_features
    self.rbm_layers[i].train(visible_data)
    hidden_features = self.rbm_layers[i].propagate(visible_data)
def fine_tune(self, data, quality_labels):
  for i in range(self.num_layers):
    visible_data = data if i == 0 else hidden_features
```

```
      hidden_features = self.rbm_layers[i].propagate(visible_data)
    self.output_layer.train(hidden_features, quality_labels)
  def predict_quality(self, data):
    for i in range(self.num_layers):
      visible_data = data if i == 0 else hidden_features
      hidden_features = self.rbm_layers[i].propagate(visible_data)
    return self.output_layer.predict(hidden_features)
Step 3: class RBM:
  def __init__(self):
    pass
  def train(self, visible_data):
    pass
  def propagate(self, visible_data):
    pass
class OutputLayer:
  def __init__(self, num_features):
    self.num_features = num_features
    self.weights = np.random.randn(num_features)
    self.bias = np.random.randn()
  def train(self, hidden_features, quality_labels):
    pass
  def predict(self, hidden_features):
    pass
def main():
   data = np.array([...])
  quality_labels = np.array([...])
  num_layers
  num_features = data.shape[1]
  qf_dbn = QF_DBN(num_layers, num_features)
  qf_dbn.pre_train(data)
  qf_dbn.fine_tune(data, quality_labels)
  test_data = np.array([...])
  predicted_quality = qf_dbn.predict_quality(test_data)
  print("Predicted quality: ", predicted_quality)
Step 4: if __name__ == "__main__":
  main()
```

IV. RESULTS AND DISCUSSION

This work uses Python 3.11 to implement a secure medical image and laptop running Windows 10 with 32 GB of RAM and an Intel (R) CPU. The effectiveness of a suggested method is contrasted with those of modern techniques such as the Mask–Region-Based Convolutional Neural Network (Mask-RCNN) [25], crossover-based Multilayer Perceptron (CMLP) model [25] and Linear Discriminant Analysis (LDA)+cuckoo search algorithm

(CSA)+Hybrid ResNet 18 and GoogleNet classifier (HRGC) model (LDA+CSA+HRGC) [26] by calculating performance measures like accuracy, precision, recall, f1-score.

System implement

A. Accuracy

Accuracy is the extent to which the recommendations and concepts offered by the platform to medical professionals are based on reliable patient data and medical knowledge. Patients can be safeguarded and improved outcomes can be attained by making informed medical decisions when the system's suggestions are reliable. The result and comparison as shown in Figure 7 and Table I and When compared to other techniques such as Mask-RCNN achieved 91%, CMLP achieved 97%, LDA+CSA+HRGC achieved 98%, and so on, the suggested method's QF-DBN value is at 99%. Compared to other ways with the same degree of Accuracy, the proposed QF-DBN performs better.

TABLE I RESULT OFACCURACY

Methods	Accuracy (%)
Mask - RCNN [25]	91
CMLP [25]	97
LDA + CSA + HRGC [26]	98
QF - DBN [Proposed]	99

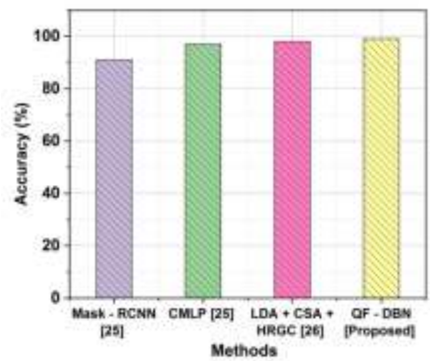

Fig.7. Comparison of Accuracy

B. Precision

Reducing the number of false positives while still offering intelligent recommendations is what defines precision. The accuracy level is calculated as a percentage of all reasonable requests that the system generates. The technology can offer medical professionals valuable recommendations without compromising the integrity of the information it provides, because of its exceptional precision. In Figure 8 and Table II, the present and recommended approaches are presented. When compared to other techniques such as Mask-RCNN attained 85%, CMLP attained 93%, LDA+CSA+HRGC attained 95.9%, and so on, and the suggested method QF-DBN value is at 97.8%. Compared to other ways with the same degree of Precision, the proposed QF-DBN performs better.

TABLE II RESULT OFPRECISION

Methods	Precision (%)
Mask - RCNN [25]	85
CMLP [25]	93
LDA + CSA + HRGC [26]	95.9
QF - DBN [Proposed]	97.8

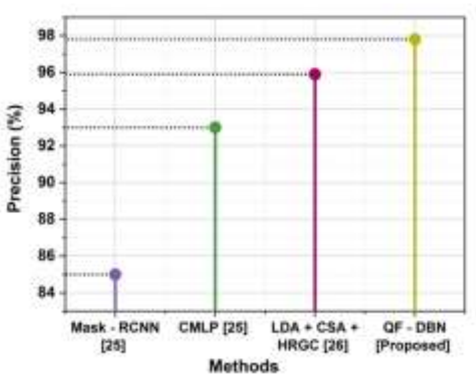

Fig.8. Comparison of Precision

C. Recall

The phrase recall is used to locate and recover all of the important data or suggestions included in the records. The ratio of correct optimistic forecasts to the total number of real positive events is known as the accuracy rate of a method. A strong recall ensures that important clinical information is noted which makes it possible to collect meaningful results and relevant metrics more efficiently. In Figure 9 and Table III, the present and recommended approaches are presented. In comparison to other approaches such as Mask-RCNN recall rate achieved 83%, CMLP recall rate achieved 92%, and LDA+CSA+HRGC achieved 95.7% recall rate, the suggested method's QF-DBN value achieved 96.28%.

TABLE III RESULT OF RECALL

Methods	Recall (%)
Mask - RCNN [25]	83
CMLP [25]	92
LDA + CSA + HRGC [26]	95.7
QF - DBN [Proposed]	96.28

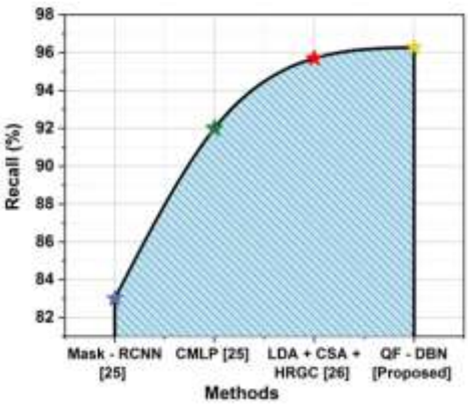

Fig.9. Comparison of recall

D. F1-score

The F1 score is one integrated statistic that takes accuracy and recall into consideration. Achieving effective optimistic forecasts and minimizing the number of false negatives are both investigated. The F1 score indicates that the algorithm can consistently offer physicians useful recommendations. A high F1 score denotes the best possible balance between accuracy and recall. In Figure 10 and Table IV, the present and recommended approaches are presented. Compared to other techniques such as Mask-RCNN, which has an F1-score of 87%, CMLP, which has an F1-score rate of 92%, and LDA+CSA+HRGC, which has a 97% of F1-score rate, the suggested approach QF-DBN has a value of 98%.

TABLE IV RESULT OFF1-SCORE

Methods	F1-Score (%)
Mask - RCNN [25]	87
CMLP [25]	92
LDA + CSA + HRGC [26]	97
QF - DBN [Proposed]	98

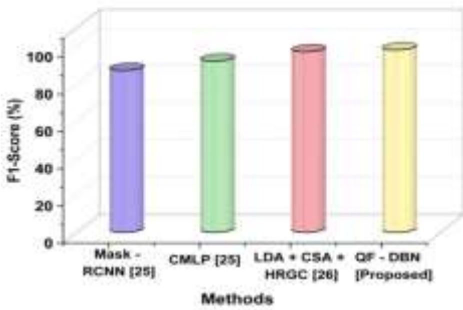

Fig.10. Comparison of F1-Score

E. Statistical analysis

Analysis utilizing the Statistical Package for the Social Sciences (SPSS) process to compare the QF-DBN and existing approaches. four independent variables are utilized variable 1 represents the Mask - RCNN method variable 2 represents the CMLP method variable 2 represents the LDA + CSA + HRGC method and variable 4 represents the QF-DBN method. The SPSS program was used to evaluate the accuracy and loss of Mask - RCNN, CMLP, LDA + CSA + HRGC and QF - DBN methods. In the comparison to the Paired Samples T-Test process, Table Vdisplays the standard deviations, significant findings, mean values, and standard errors for the pairs of variables before and after improvement using the QF-DBN. It is crucial to understand the mean values since the Paired Samples Test compares the means of the four variables. A T-test with a small significant value (usually less than 0.05) suggests that the two variables vary from one another. The acquired t-test result is (0.002), indicating that the QF-DBN approach produced substantial results on test accuracy. This circumstance was highlighted in the estimate measures.

TABLE V COMPARISON RESULTS OFT-TEST

Methods	Mean	Std deviation	Std error mean	T	DF	Sig-value
Mask - RCNN [25]	93	4.326	4.823	17.2	2	0.003
CMLP [25]	87.3	4.125	4.263	18.2	3	0.004
LDA + CSA + HRGC [26]	96	3.123	3.355	18.9	4	0.005
QF - DBN [Proposed]	97.8	2.369	2.226	20.2	2	0.002

F. Real time environment

In an actual-global IoT-cloud-pushed healthcare machine, statistics conversation includes more than one ranges and technologies to ensure efficient, secure, and reliable transfer of health data from medical sensors to the cloud and eventually to healthcare providers or end-users. The workflow begins with gather information, where clinical sensors and wearable device acquire physiological information (e.g., glucose stages, coronary heart charge, blood pressure) from sufferers in actual-time. This records is then transmitted to local devices which includes smartphones or gateways through Bluetooth or Wi-Fi. Next, facts transmission to the cloud through internet protocol like HTTP/HTTPS over cell networks, making sure steady transmission with encryption (TLS/SSL). In the cloud, data undergoes preprocessing steps like normalization and filtering to take away noise, observed by storage in scalable cloud databases. The cloud platform then uses techniques together with Linear Discriminant Analysis (LDA) to extract applicable features and applies the Quality-conscious Feature-tuned Deep Belief Network (QF-DBN) model to diagnose diabetes and assess its severity. The evaluation consequences are communicated to stop-customers thru notifications and alerts via mobile apps, electronic mail, or SMS, and a person dashboard affords specified fitness reports.

G. Discussion

Real-time monitoring of heart failure patients is made possible by a suggested smart healthcare architecture that combines cloud and IoT technology. IoT-based sensors are used by the framework to gather the status of cardiac patients. The cloud unit receives these signals after which they are processed further. The deep model uses signals to determine if the patient is still alive. Mask-RCNN's [35] real-time usefulness in IoT-cloud-based smart healthcare monitoring systems is limited by its high computational complexity and resource requirements. Large datasets are also needed for training, which might provide difficulties with data collection and annotation, especially in contexts like hospitals where privacy is an issue. In IoT-cloud-based smart healthcare monitoring systems, CMLP [35] models can develop over fitting while handling complicated information. Furthermore, the selected architecture and hyper parameters, which can be difficult to optimize, particularly in dynamic healthcare situations, have a significant impact on their performance. The scalability and flexibility of the LDA+CSA+HRGC [36] technique to a variety of healthcare datasets can be limited. Its inability to accurately capture complex linkages across diverse data sources might be a hindrance to its usefulness in real-world smart healthcare applications. Furthermore, combining several methods adds to the complexity and computational costs, which can affect deployment viability and efficiency. QF-DBN integrates quality awareness and feature tailoring to overcome shortcomings. Moreover, feature tuning enhances the architecture of the network and improves its capacity to extract pertinent data, hence boosting the performance of IoT-cloud-based smart healthcare monitoring systems.

V. CONCLUSION

Healthcare with IoT capabilities provides millions of people with web-based features and health support. These applications are essential to the advancement of healthcare for improved well-being and lifestyle since they manage enormous amounts of data and use CC for secure archiving. A novel cloud-based and IoT mobile healthcare application has been developed and implemented to monitor the extent of severe illness and diagnose patients based on severity. In this case, a new framework has been made available to the public.Furthermore, a novel classification technique known as the quality-aware feature-tuned deep belief network (QF-DBN) classifier for diabetes illness diagnosis and severity has been presented.The medical data will be created by utilizing medical sensors and open-source datasets to identify individuals who are likely to have severe diabetes. Min-max normalization is used in the data preprocessing to enhance the data by removing noisy data. The third stage involves determining the set of features through the use of linear discriminant analysis (LDA). The results of the experiment show that the recommended approach performs better than the existing sickness prediction systems. To analyze the proposed strategy employing several measures, including accuracy (99%), precision (97.8%), recall (96.28%), and F1 score (98%), the finding assessment step will evaluate the proposed model's detection capability. When evaluated on the diabetes standard dataset, the T-test statistical approach produced considerable improved outcomes using the QF-DBN methodology. Future research in this area can involve introducing strong security measures that make use of cutting-edge cryptographic techniques to improve the security of medical data stored in cloud databases.

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