IOT AND CLOUD BASED MEDICAL DISEASE DIAGNOSIS AND CLASSIFICATION MODEL USING OPTIMAL KERNEL EXTREME LEARNING MACHINE

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ABSTRACT

Due to the development of Internet of Things (IoT) and related devices in the healthcare sector, diverse set of medical applications and services becomes feasible. The massive quantity of healthcare data produced by IoT devices requires cloud computing platform for handling it. This paper presents a new IoT and Cloud Enabled Disease Diagnosis and Prediction Model using Teaching and Learning based Optimization (TLBO) Algorithm with Kernel Extreme Learning Machine (KELM), named TLBO-KELM model. The proposed model initially performs data collection, where the acquisition of healthcare data takes place using three sources such as IoT devices, benchmark data repositories, and medical records. Then, the TLBO-KELM model gets executed to diagnose and predict the existence of diseases using the patient data. Besides, the application of TLBO algorithm in KELM helps to effectively tune the parameters for achieving better classification performance. The performance of the TLBO-KELM model has been tested against benchmark pimaindian diabetes dataset. The simulation outcome ensured that the TLBO-KELM model has outperformed the earlier models in a significant manner.

Keywords: Cloud, Classification, Disease Diagnosis Healthcare, IoT, TLBO Algorithm

1. INTRODUCTION

Basically, IoT and Cloud Computing (CC) methods are highly productive and while them are combined, then the merits attained are tremendous. Here, patient details can be observed even at the far away distance that is been highly beneficial for the doctors. IoT model is applicable in CC which improves the function with respect to higher resource consumption, memory, power and processing ability. Additionally, CC gathers the attention from IoT by extending the range of ability to handle real-time applications dynamically. The unification of CC and IoT based web applications performs quite well when compared with normal CC domains by means of effectiveness. Some of the domains that acquire the benefit from this combination are healthcare, armed forces, banking sectors and several other applications. In particular, the CC reliedIoT method would be more adoptable in giving resourceful services in clinical sections by observing and retrieving the data whenever it is essential. IoT based medical fields are applied for gathering desired information like modified health variables and seriousness of clinical parameters are extended at the provided time interval. Moreover, IoT tools and clinical attributes based sensor readings would be employed for exact disease analysis in correct time by preventing the fatal situation. In line with this, Machine Learning (ML) approaches are most significant in making decisions while managing massive amount of data.

The task of using data analyzing models only at certain regions has 3 data types such as Velocity, Variety and Volume. The benchmark data analysis methods are Neural Network (NN), Classification and Clustering approaches, and other supplement frameworks. Data could be produced from different points using specific data types and it is mandatory to create techniques with potential of handling data features. For IoT, essential data can
be created practically without any interruptions like scalability, velocity and explores the optimal method. The above-mentioned problems are assumed to be major issues in IoT. Hence, these problems can be resolved by developing new technologies. Here, maximum amount of big data is collected with diverse data types like image, text, and definite data by IoT tools as input data. Such data might be recorded in CC platform in secured manner which can be applied by newly deployed medical sectors. At this point, novel ML model is applied for mapping the data into 2 categories like 'Normal' and 'Abnormal'.

In past decades, maximum frameworks have been introduced in different studies. Initially, [1] deployed a novel approach for predicting the severity of disease and examined by CC and IoT. This application is often employed for screening the health of students. In this approach, a programmatic health data has been produced under the application of best UCI Repository, and sensors [2]. It is employed in medical field to detect the diseases that exist in students. Diverse classification modules were utilized to predict disease types. The prediction accuracy has been determined with the help of attributes like F-measure, specificity and sensitivity. As a result, it is approved that this method performs quite well with respect to prediction accuracy.

This paper develops an efficient IoT and Cloud Enabled Disease Diagnosis and Prediction Model using Teaching and Learning based Optimization (TLBO) Algorithm with Kernel Extreme Learning Machine (KELM), named TLBO-KELM model. The proposed model initially performs data preprocessing, where the acquisition of healthcare data takes place in three sources such as IoT devices, benchmark data repositories, and medical records. Then, the TLBO-KELM model gets executed to diagnose and predict the existence of diabetes and DR using the patient data. In TLBO-KELM algorithm, the parameter optimization of KELM takes place by TLBO algorithm. A series of simulation analysis takes place for ensuring the goodness of the TLBO-KELM algorithm.

II. RELATED WORKS

This section briefs a survey of different CC and IoT based disease diagnosis models in healthcare sector. [3] carried out a review on CC and IoT methods with protective issues. Then, the role of CC in IoT is depicted. A modelled and established a fresh multi-layer cloud that activates the efficiency the seamless communications across heterogeneous services offered by dissimilar vendors in smart home. Furthermore, ontology is applied to resolve the heterogeneity problems in layered cloud platform. [4] introduced a new and reliable 3 tier structure to save massive amount of sensor data. At the earlier stage, Tier-1 performs data gathering task. Then, Tier-2 records every sensor data in CC effectively. Followed by, a novel detection approach for Heart Diseases (HD) has been evolved. Lastly, ROC analysis is carried out to find the signs of getting HD.

[5] presented a novel approach for CC for managing the recent IoT data and scientific data that are non-relevant to IoT. An effective Cyber Physical System to support the multi-sites as well as multi-products development. [6] applied a new idea in car camera system that uses mobile CC model for Deep Learning (DL). It forecasts the objects present in saved videos at the time of car driving which selects specific portion of videos that is saved in CC. [7] focused in developing novel cloud relied parallel ML model for machinery prognostics. The Random Forest (RF) method is employed for the prediction of the tool wear in dry milling task. Additionally, a parallel RF is manufactured with the help of MapReduce. It is clear that, RF classification model is applicable to predict an exact accuracy. [8] Compute the process of observing voice pathology under the application of CC and IoT. [9] Argues the fundamentals of IoT with applicable features in u-healthcare. Additionally, a novel approach is helpful for IoTRelied u-healthcare service. This method is suitable for performance increment of medical service.

[10] defined regarding IoT clinical devices in body area sensors. Here, a patient could be observed with the application of minimum powdered and lightweight sensor networks. Furthermore, it is assumed the security demands to develop healthcare system. [11] Discussed the vision of structural components as well as future directions of IoT module. A web monitoring approach named as Healthcare Industrial IoT that monitors the health system. It is applicable to analyze the patients’ health details by eliminating the patient's fatality. Furthermore, it gathers the related patient details that are essential to analyze with the help of sensors and the clinical tools. It is defined several models that is applied in direction of m-healthcare.

The domains like website developer is applied for monitoring patient’s health status under the application of IoT relied system. [12] Presented a people-based sensing approach for analyzing the disease in older and handicapped people. The intention of this method is to offer a service-based emergency reply for diseased peoples. A smart and collaborative security method to reduce the risks in an IoT enabled healthcare platform. Moreover, it is examined with IoT advancements in medical sector. [13] Presented a smart medical diagnosing mechanism
named as neuro-fuzzy temporal knowledge representation which helps in detecting and analyzing different types of mortal disease. Additionally, the intelligent as well as best fuzzy rule relied classification method was projected by [14]. At the same time, diabetes is a commonly occurring disease which affects people all over the globe. Several diabetes diagnosis models have been developed and available in the literature [15-18].

III. THE PROPOSED MODEL

The working principle of the TLBO-KELM is illustrated in Fig. 1. The wearables and attached IoT devices are treated as data collectors, which are used to acquire data from remote regions. The direct readings can be accumulated from patient data, which are collected by the IoT devices linked to the human body. Besides, medical dataset comprises the past details of the patients gathered by healthcare centers. It undergoes preprocessing to convert the data into compatible data format. It is also saved in the cloud database for flexible accessibility. Finally, TLBO-KELM model gets executed to determine the presence of disease.

3.1. Preprocessing

The input data gathered by the IoT devices are preprocessed in the initial stage. During preprocessing, the input data in diverse format are converted into .arff format to make it compatible for further processing. Next to that, the preprocessed data will be classified by the use of TLBO-KELM model.

3.2. TLBO-KELM Model

In recent times, KELM has gained an extensive growth. It is revolutionized from ELM and it provides maximum normalization in real-time applications. ELM is a single-hidden-layer feed-forward NN (FFNN) and generalize SLFNs with no tuning parameters present in hidden layer as well. The resultant function of ELM for generalized SLFNs is depicted in Eq. (1), by assuming the output node as an instance [19]. Fig. 2 shows the architecture of KELM method.

\[ f_L(x) = \sum_{i=1}^{L} \beta_i h_t \tilde{d}_i(x) = h_t \tilde{d}(x) \beta \]  

(1)

Where, \( \beta = [\beta_1, \beta_2]^T \) is the vector of output weights among hidden layer of \( L \) nodes and output node, while output vector of hidden layer along with relevant input \( x \) is depicted as \( \tilde{h}_t(x) = [\tilde{h}_t(x_1), \tilde{h}_t(x_2), \ldots, \tilde{h}_t(x_N)] \). Next, a dataset undergoes mapping from \( d \)-dimensional input space to the \( L \)-dimensional hidden layer feature space \( HID \) based on the \( \tilde{h}_t(x) \), that shows that \( \tilde{h}_t(x) \) is a feature mapping.

To accomplish minimum training error of FFNN and if the weights are smaller, then the generalization functions are normal. ELM is mainly applied to reduce the training error and norm of output weights at the same time.

\[ \min ||HID\beta - T||^2 \text{ and } ||\beta|| \]  

(2)

\[ HID \text{ of previous formation refers the hidden-layer output matrix} \]

\[ HID = \begin{bmatrix} \tilde{h}_t(x_1) \\ \tilde{h}_t(x_2) \\ \vdots \\ \tilde{h}_t(x_N) \end{bmatrix} = \begin{bmatrix} \tilde{h}_t(x_1) & \cdots & \tilde{h}_t(x_N) \\ \vdots & \ddots & \vdots \\ \tilde{h}_t(x_1) & \cdots & \tilde{h}_t(x_N) \end{bmatrix} \]  

(3)

The original semantics of reducing output weights \( ||\beta|| \) is to improvise the distance of classifying margins of various classes in ELM feature space. The tiny normal least square models are employed in ELM

\[ \beta = HID^T T \]  

(4)
Where $HID^\dagger$ is the Moore-Penrose normalized inverse of matrix.

The actual factor pointed here is, if users are unaware of feature mapping, then Kernel matrix has been applied named as Kernel mapping function for ELM which is acquired by using the function:

$$\Omega_{ELM} = HID^\dagger \cdot \Omega_{ELM} = hid(x_i) \cdot hid(x_j) = K(x_i, x_j)$$

(5)

where $hid(x)$ denotes a mapping function that maps data form input space to confirm linearly separable in hidden-layer feature space HID. The orthogonal representation models are used to determine the MP generalized matrix’s inverse, like $HID^\dagger = HID^T (HIDHID^T)^{-1}$, as well as a positive constant $C$ is projected to diagonal of $HIDHID^T$. Hence, ELM’s output function is expressed as:

$$F(x) = hid\beta = hid(x)HID^\dagger (\frac{1}{C} + HIDHID^T)^{-1} T$$

(6)

The people do not have the knowledge of hidden layer features, that is equalized with the kernel trick, and radial basis function (RBF) is applied. It is often described as $(x, x_i) = \exp (-\gamma ||x - x_i||^2)$. There are 2 critical attributes in RBF kernel are:

- Penalty parameter $C$
- Kernel parameter gamma $\gamma$.

These two parameters need to be carefully selected, which is optimized by the use of TLBO algorithm.
A novel intelligent mechanism named as TLBO [20] is used to resolve the mathematical optimization issues. In this technique, the population is named as set of learners (nPops) and better potential solutions for optimization issues are assumed as a teacher from entire class. The main goal of TLBO method is to identify good learner by cooperation and data distribution among the students. The performance of TLBO method is based on highly comfortable learners, thus it produces best simulation outcome. The entire population is expressed as a vector as shown in Eq. (7).

\[ X_{i,k} = \begin{bmatrix} \chi_{1,1} \\ \vdots \\ \chi_{1,n} \\ \vdots \\ \chi_{n,1} \\ \vdots \\ \chi_{n,n} \end{bmatrix} \]  

(7)

Where, \( i \) denotes the count of populations, \( K \) refers dimension of an issue, and \( \chi_{i,k} \) signifies the location of \( i^{th} \) learner in \( K^{th} \) dimension. The learner \( X \) is initialized randomly inside a search space. The deployment of \( \chi_{i,k} \) is produced arbitrarily in the Eq. (8).

\[ \chi_{i,k} = L_k + r_1 \times (U_k - L_k) \]  

(8)

Where, \( i = 1, 2, 3, \ldots, nPop \), \( K = 1,2,3 \), \( D, r_2 \) are uniform random values among 0 and 1, \( L_k \) is lower bound value, and \( U_k \) means upper bound value. TLBO task is divided into 2 stages. Initially, a teacher phase: the students may gather knowledge from a teacher, while in learner phase: the student gains knowledge by communicating among others. The fundamental model of TLBO is defined in the following subsections.

**Teacher phase**

First, a teacher tries to evolve the learners and improvise the Knowledge level. But it is not feasible practically, and a teacher can enhance the mean Knowledge of class to limited extent according to the students’ potency. Assume \( M_{\chi}(i,k) = \frac{1}{n} \text{Pop} \sum_{i,k} \chi_{i,k} \) be a mean value of certain subject, where \( k = 1,2,\ldots,D \). The extending equation of is depicted in Eq. (9).

\[ x_{i,k}^{\text{new}} = x_{i,k}^{\text{old}} + r_2 \times (x_{\text{teacher},k} - T_{f} \times M_{i,k}) & T_{f} = \text{round}[1 + \text{rand}(0,1)] \]  

(9)

Here, \( x_{\text{teacher},k} \) are optimal learner of applied population at previous round of Algorithm, \( r_2 \) denotes a random value from [0,1]; and the measure of \( T_{f} \) may be 1 or 2.

**Learner phase**

Secondly, the Knowledge of learners can be boosted by exchanging between the students and also the teacher’s experience. The main aim of a learner is to communicate randomly with co-learners and improve communication
ranks. Besides, the \( t \)th learner is chosen as \( X_p \) and other random learner as \( X_q \) by mutual interaction with learners. The updating function of \( i \)th learners \( X_p \) and \( X_q \) can be defined.

\[
\text{for } i = 1 \text{ to } n \text{ select two learners } X_p \text{ and } X_q \\
\text{ if } (f(X_p) < f(X_q)) \\
\quad \text{new} \ X_i = \text{old} \ X_i + r \times (X_p - X_q) \\
\quad \text{Else} \\
\quad \text{new} \ X_i = \text{old} \ X_i + r \times (X_q - X_p) \\
\text{end if} \\
\text{end for}
\]

Where \( r \) is a random measure from \([0, 1]\), \( f(X_p) \) and \( f(X_q) \) refers optimal solutions of learners \( X_p \) and \( X_q \).

Concerning the learner group size is \( nPop \), while learner interacts to gain the sufficient Knowledge. Such phenomena are used to enhance the performance of TLBO model to best searching area with supreme outcome.

3.4. Parameter Optimization of KELM using TLBO algorithm

The feature of KELM is managed using 2 parameters of \( \zeta \) and \( \gamma \). Here, it is established by TLBO algorithm, which identifies 2 parameters in KELM. The final evolutionary KELM model termed as TLBO-KELM, applies TLBO principle to compute the 2 parameters in KELM. TLBO-KELM is comprised of 2 procedures such as parameter optimization as well as classification property estimation. While computing the parameter optimization, 10-fold CV is carried out on last set. The inner parameter optimization is stopped, and then optimal parameter pair has been induced into KELM prediction approach and process the classification task for disease diagnosis. The classification accuracy is assumed while developing the fitness function as follows:

\[
\text{Fitness Function (Average Accuracy)} = \frac{\sum_{n=1}^{N} Test_{Accuracy}(n)}{N}
\]  

(10)

where average accuracy in fitness function refers the testing, accuracy attained by KELM classifier by 10-fold CV model by inner parameter optimization strategy.

IV. PERFORMANCE VALIDATION

4.1. Dataset used

The performance of the TLBO-KELM model has been tested using PIMA Indians Diabetes [21]. The information related to the dataset is provided in Table 1. The frequency distribution of the attributes exists in the applied data set are shown in Fig. 3. Sample screenshots obtained during experimentation is given in Appendix.
### Table 1 Dataset Description

<table>
<thead>
<tr>
<th>Description</th>
<th>Pima Indian Diabetes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Instances</td>
<td>768</td>
</tr>
<tr>
<td>Number of Attributes</td>
<td>8</td>
</tr>
<tr>
<td>Number of Class</td>
<td>2</td>
</tr>
<tr>
<td>Percentage of Positive Samples</td>
<td>34.90</td>
</tr>
<tr>
<td>Percentage of Negative Samples</td>
<td>65.10</td>
</tr>
<tr>
<td>Data sources</td>
<td>[21]</td>
</tr>
</tbody>
</table>

#### 4.2. Performance Measures

A set of measures used to investigate the outcome of the TLBO-KELM model are sensitivity, specificity, accuracy, F-score and kappa value.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{11}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \tag{12}
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}
\]
F - Score = \frac{2TP}{2TP + FP + FN} \tag{14}

Kappa value = \frac{(Observed Agreement - Chance Agreement)}{(100 - Chance Agreement)} \tag{15}

where, \quad Chance Agreement = \left(\% (TP + FP) \times \% (TP + FP)\right) + \left(\% (TP + FP) \times \% (TP + FP)\right) \quad \text{and} \quad Observed Agreement = \% (Overall Accuracy).

4.3. Results Analysis

In this section, the classifier outcome of the TLBO-KELM model under benchmark diabetes dataset has been investigated in detail. Table 2 provides the comparative results analysis of the KELM with TLBO-KELM models on the applied PIMA Indians Diabetes dataset.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
<th>F-score</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>TLBO-KELM</td>
<td>94.00</td>
<td>85.82</td>
<td>91.15</td>
<td>93.25</td>
<td>80.38</td>
</tr>
<tr>
<td>KELM</td>
<td>91.20</td>
<td>72.76</td>
<td>84.77</td>
<td>88.63</td>
<td>65.61</td>
</tr>
</tbody>
</table>

Fig. 4 investigates the sensitivity analysis of the TLBO-KELM model with the existing KELM model on the PIMA Indians Diabetes dataset. The figure showcased that the TLBO-KELM model has achieved improved sensitivity of 94% whereas the KELM model has obtained slightly reduced sensitivity of 91.20%.

Fig. 5 examines the specificity analysis of the TLBO-KELM model with the existing KELM model on the PIMA Indians Diabetes dataset. The figure depicted that the TLBO-KELM model has accomplished enhanced specificity of 85.82% whereas the KELM model has gained slightly reduced specificity of 72.76%.

![Fig. 4. Sensitivity analysis of TLBO-KELM model on PIMA Indians Diabetes dataset](image-url)
Fig. 5. Specificity analysis of the TLBO-KELM model on PIMA Indians Diabetes dataset

Fig. 6 inspects the accuracy analysis of the TLBO-KELM model with the existing KELM model on the PIMA Indians Diabetes dataset. The figure displayed that the TLBO-KELM model has reached to an increased accuracy of 91.15% whereas the KELM model has resulted to a decreased accuracy of 84.77%.

Fig. 6. Accuracy analysis of the TLBO-KELM model on PIMA Indians Diabetes dataset
Fig. 7. F-score analysis of the TLBO-KELM model on PIMA Indians Diabetes dataset

Fig. 7 studies the F-score analysis of the TLBO-KELM model with the existing KELM model on the PIMA Indians Diabetes dataset. The figure showcased that the TLBO-KELM model has achieved improved F-score of 93.25% whereas the KELM model has obtained slightly reduced F-score of 88.63%.

Fig. 8. Kappa analysis of the TLBO-KELM model on PIMA Indians Diabetes dataset

Fig. 8 demonstrates the kappa analysis of the TLBO-KELM model with the existing KELM model on the PIMA Indians Diabetes dataset. The figure portrayed that the TLBO-KELM model has achieved enhanced kappa of 80.38% whereas the KELM model has attained somewhat reduced kappa of 65.61%.
Table 3 Comparison with Recent Methods in terms of Accuracy for Diabetes Dataset

<table>
<thead>
<tr>
<th>References</th>
<th>Classifiers</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>TLBO-KELM</td>
<td>91.15</td>
</tr>
<tr>
<td>Dash et al., 2019 [22]</td>
<td>TLBO+RBFN</td>
<td>66.66</td>
</tr>
<tr>
<td>Dash et al., 2019 [22]</td>
<td>iTLBO+RBFN</td>
<td>81.77</td>
</tr>
<tr>
<td>Lv and Han, 2018 [23]</td>
<td>Rotation Forest</td>
<td>67.20</td>
</tr>
<tr>
<td>Lv and Han, 2018 [23]</td>
<td>ROF+KELM</td>
<td>78.91</td>
</tr>
</tbody>
</table>

Fig. 9. Comparison of TLBO-KELM with recently proposed models on PIMA Indians Diabetes Dataset

Table 3 and Fig. 9 provide a comparative analysis of the TLBO-KELM model with recently proposed models [23-27] on the diabetes dataset. The table values indicated that TLBO+RBFN, Rotation Forest and ROF+KELM models have failed to show acceptable classifier outcome by ending up with the accuracy values of 66.66%, 67.20%, and 78.91% respectively. On continuing with, the iTLBO+RBFNmodel has exhibited somewhat manageable classifier results with the accuracy of 81.77%. But the proposed TLBO-KELM model has achieved better outcome over the recently proposed models with the accuracy of 91.15%. The overall experimental results clearly portrayed the maximum diabetes disease classification of the TLBO-KELM model over the compared methods.

V. CONCLUSION

This paper has introduced a new IoT and Cloud Enabled Disease Diagnosis and Prediction Model TLBO-KELM model. The proposed model initially performs data preprocessing, where the acquisition of healthcare data takes place in three sources such as IoT devices, benchmark data repositories, and medical records. Then, the TLBO-KELM model gets executed to diagnose and predict the existence of diseases using the patient data. The performance of the TLBO-KELM model has been tested using PIMA Indians Diabetes dataset. The simulation outcome indicated that the TLBO-KELM model has attained maximum accuracy value on the applied dataset. Therefore, the TLBO-KELM model can be employed as an effective tool for automated disease diagnosis using IoT and cloud environment. In future, the performance of the TLBO-KELM model can be improved by the use of clustering and feature selection techniques.
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