

Federated Learning-Based Disease Diagnosis and Treatment Recommendation System Using Blockchain

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***Abstract*—In the medical field, significant changes have been provided by advancements in technology. But, owing to the higher scalability of modern healthcare networks and growing data privacy concerns, centralized collection and processing of medical data are infeasible. Hence, this work proposes Federated Learning-based Disease Diagnosis and Treatment Recommendation System (FL-DDTRS) with blockchain. Primarily, from the patients with IoT devices, attributes are extracted, which are then fed into the local model named the Disease Diagnosis and Treatment Recommendation System (DD-TRS) system. DD-TRS data obtained from the patient's discharge summary dataset is pre-processed and the medical term is identified. After that, the score value for the obtained medical term is determined via Pearson Chi-Square Fuzzy-Clinical Bert Embedding (PCSF-CBE). Grounded on the value, the disease is diagnosed and treatment details are provided by Swish-Entropy-based Gated Recurrent Unit (S-EGRU). For future reference, the classification output in the local model is updated in the Global training model. Likewise, the attribute extracted is encoded via Kullberg Leibler Divergence-based Diversity (KLD-Diversity) algorithm. By utilizing Reverse Digit Folding based Tiger Hashing (RDF-Tiger) algorithm, the encoded data is stored in Interplanetary File System (IPFS), which is then placed in the blockchain for verification. Lastly, for validating the proposed technique's superiority, its performance is contrasted with the prevailing approaches.**

Keywords: *Health data, disease detection, recommendation, global model, federated learning***.**

1. INTRODUCTION

The health of a human being is of primary concern in order to lead a peaceful and successful life. Thus, the appropriate collection, organization, and utilization of health information aids in effective medical complication detection and results in innovative solutions' identification

[1] Owing to the availability of a huge amount of clinical data, there is a rising requirement for effective mining models to help with disease diagnosis and enhance medical care for patients[2]. Hence ,the development of computer technologies has made more and more healthcare data gathered from clinical institutions, and pharmaceutical industries to be readily available for analysis [3]. In the Healthcare department, the patient's records are stored in the centralized Electronic Health Record (EHR) system for monitoring and delivering uninterrupted real-time services [4].In general, clinical data generated from numerous sources is wielded for disease recognition [5].Thus, developing an efficient technique to handle the data characteristics is essential. Previously, for collecting data from a powerful cloud machine, centralized training techniques are utilized, which in turn resulted in user privacy leakage[6]. Machine Learning (ML) techniques are utilized as an effective tool in numerous fields, including healthcare with powerful computation capabilities [7] But, training ML models with abundant health data affected disease recognition accuracy. Therefore, Federated Learning (FL)-centered treatment Recommendation System (RS) is proposed utilizing PCSF-CBE and S-EGRU techniques in IPFS and blockchain. A technique that trains Internet of Things (IoT) devices in a decentralized way utilizing certain algorithms without leaking the privacy of the diseased ones is named FL[8], [9] . Also, by considering the safety aspects of accessing the data, the usage of blockchain in the healthcare domain provided a new dimension to the healthcare market [10].

A. Problem Statement

Despite the advantages provided by the prevailing treatment recommendation techniques, there exist certain limitations as,

- Prevailing research methodologies failed to concentrate on the resource learning process.
- In the conventional system, server storage and the non-uniformity of user distribution resulted in higher network delay.
- Previously, the patient history is retrieved utilizing third-party software, which resulted in a lack of security.

Hence, to alleviate the aforementioned issues, an FL- DDTRS is proposed and its main contributions are,

- The global model in the FL provided detailed patient information.
- Blockchain is wielded for storing the patient attributes utilizing hash values, which avoided unwanted delay.
- The privacy of the patients is well maintained by utilizing the KLD-Diversity technique.The remaining part is arranged as: the related works are elucidated in Section 2; the proposed system is explicated in Section 3; the outcomes are illustrated in Section 4; lastly, the paper is winded up in Section 5.

II. LITERATURE SURVEY

Propounded a lightweight FL approach for the efficient management of healthcare data utilizing blockchain. Here, by utilizing Software Guard Extensions-Trusted Execution Environment (SGX-TEE), the local model's aggregation was performed. Hence, biasing and privacy leakage were efficiently avoided. But, the data management accuracy was degraded by the introduction of noise. [11]

Proffered Random Forest (RF) technique-centric RS. Here, utilizing the ML approach, the data collected was evaluated and forwarded to medical experts via wireless connections. Thus, the resources were efficiently scheduled with better patient interactivity by this technique. Conversely, the presented approach was suitable only for a limited number of datasets. [12]

Recommended an Ensemble Learning (EL)-centered Health Fog (HF) technique for disease recognition. Here, the healthcare data was delivered as a fog service utilizing IoT devices; also, the data was efficiently managed as per the user's request. The outcomes proved the developed model's efficacy. However, owing to the increment in the time taken for processing the user request, the latency was increased. [13]

Employed Bidirectional Long Short-Term Memory (Bi-LSTM)-based healthcare data monitoring. Here, the various steps involved were pre-processing, dimensionality reduction, Semantic knowledge determination, and classification. Thus, this approach effectively handled the heterogeneous data. However, the presented system was not suitable for real-time analysis. [14]

Presented Data fusion-based EL treatment RS. Pre-processing, feature extraction, feature fusion, and classification were the steps involved here. Hence, this work completely avoided the overfitting problem.

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Conversely, performing classification without selecting the optimal features affected the performance of this mechanism. [15]

Propounded Ensemble Deep Learning (EDL) and feature fusion-centric disease RS. Primarily, the data was collected utilizing EDL, followed by feature extraction utilizing Framingham Risk Factors (FRF), feature fusion, and classification of healthcare data. Therefore, to provide better recommendations, data was effectively combined with the extracted features. However, the recommendation accuracy was affected by the usage of the limited number of features for disease recommendation. [16]

Explored Federated Transfer Learning (FTL) approach in healthcare applications. Here, the crucial steps involved were data aggregation, parameter learning, and classification. Accordingly, the data islanding and personalization problem was effectively avoided by this framework. On the contrary, personalization and privacy security issue was the major concern of this technique. [17]

III. PROPOSED DISEASE DIAGNOSIS AND TREATMENT RECOMMENDATION SYSTEM

Providing compatible treatment schemes for diseases centered on their symptoms at different stages is essential in the medical field. Thus, an FL-based technique is proposed and its framework is elucidated in Figure 1.

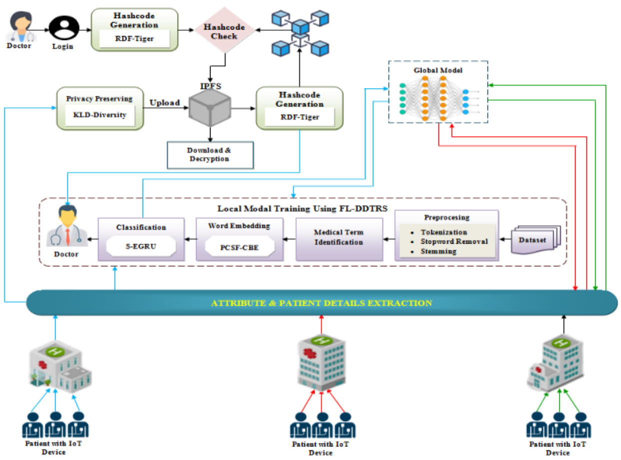

Fig. 1. Block diagram of the proposed framework.

A. Attribute Extraction

Primarily, from the patients, crucial attributes are extracted. Hospital ID, Patient ID, Name, Age, Sex, Contact Number, Address, Symptoms, Temperature, and Blood Pressure are the attributes extracted from the patients with IoT devices. Hence, the n – number of attributes is, Shown in the following Equation

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$$E^i = E^1, E^2, E^3, \ldots, E^n + n_0 \qquad \ldots (1)$$

Where, E^i signifies the attributes extracted, and n_0 implies the noise.

B. Local model training using FL-DDTRS

For the efficient characterization of the disease, the extracted attributes are then forwarded to the local model. The local model training involves the following stages.

a)Pre-processing

Here, the data obtained from the discharge summary dataset is pre-processed to make it suitable for further processing. The pre-processing steps are,

- *Tokenization:*

  It is the process of splitting the incoming attributes into other meaningful elements called tokens. Hence, the data obtained after tokenization is T^d.

- *Stop word removal*

  To eliminate words that frequently appear in a document, stop word removal is carried out. It is modelled as S^w

- *Stemming*

  Then, the stemming is done, which reduces words to their shortest form and is represented as $\hat{S}^t$. Hence, the output obtained after pre-processing is given as,

$$P^p = \{T^d, S^w, \hat{S}^t\} \qquad \ldots (2)$$

b) Medical Term Identification

Next, from the pre-processed output, medical terms are identified. Thus, $m-$ number of medical terms effectively-identified (M^j) is given as,

$$M^j = M^1, M^2, M^3, \ldots, M^m \qquad \ldots (3)$$

c) Word embedding via PCSF-CBE

Afterward, for the identified medical terms, score values are determined using PCSF-CBE. To give better-summarized results than the other algorithms, Clinical Bidirectional Encoder Representations from Transformers (CBE) are used. Nevertheless, the misclassification problem will be caused by the training of unstructured data. Thus, Pearson Chi-Square-based Fuzzy algorithm is amalgamated with traditional CBE. The steps involved in PCSF-CBE are,

Step 1: Initially, M^j are converted into fuzzy sets using the membership function (ς^{pc}) obtained using the Pearson correlation technique and is defined as,

$$\varsigma^{pc} = \frac{\chi(M^j, M^m)}{\eta(M^j M^m)} \qquad \ldots (4)$$

Where, $\chi(M^j, M^m), \eta(M^j M^m)$ describes the correlation and mean value between the j^{th} and m^{th} term. Next, a divergence determined using Chi-Square (ς^{chi}) is given as,

$$\varsigma^{chi} = \tau\left(\tau v, (\tau v + fv) +^{prob}\right) + \tau\left(f\hat{n}, (f\hat{n} + \tau\hat{n}) +^{prob}\right) + \tau\left(fv, (\tau v + fv) -^{prob} + \tau(\tau\hat{n}, f\hat{n} + \tau\hat{n}) -^{prob}\right) \quad \ldots (5)$$

Here, $+^{prob}, -^{prob}$ implies the positive and negative class probability and $\tau v, \tau\hat{n}, fv, f\hat{n}$ signifies the true positive true negative, false negative and false positive.

Step 2: Then, the rule (δ) which is more suitable for the incoming M^j is determined.

$$\delta = (\varsigma^{pc} OR \varsigma^{chi}) \qquad \ldots (6)$$

Step 3: In the end, to transform the fuzzy values into crisp terms, defuzzification is done. Here, the crisp output (C^o) is obtained as,

$$C^o = \{C^1, C^2, C^3, \ldots, C^N\} \qquad \ldots (7)$$

Here, $o = 1,2,3,\ldots,N$ denotes the crisp values for the identified medical terms. To summarize the output-scored sentences, the crisp values thus obtained are fed into the input layer of PCSF-CBE.

Step 4: The token for each crisp value $[CLS]$ is determined in the input layer. Each $[CLS]$ is separated by the separation function $[SEP]$. The token thus obtained is then forwarded to the embedding layer, where the tokens are mapped into numerical vectors. The numerical vector thus obtained is the sum of word, position, and segment embedding.

Step 5: The token, segment, and position embeddings are given to the BERT transformer encoder layer. The encoder encodes the words and the decoder determines the significant keywords and gives contextual embeddings.

Step 6: Next is the summarization layers, where the scores of the medical terms are estimated and the high-scored terms are given as summarized output, which is depicted as,

$$B^k = \phi\{B^1, B^2, ..., B^K\} \qquad \dots (8)$$

Here, B^k implies the summarized output score value and $\phi(\ )$ signifies the sigmoid function.

d) *Classification through S-EGRU*

Finally, classification is done using S-EGRU. Gated Recurrent Unit (GRU) has gating mechanisms that aid in the control and management of classification accuracy. But, gradient diffusion problems are caused by the dependence of the generalization performance on the activation function. Thus, the S-EGRU is defined and its structure is displayed in Figure 2.

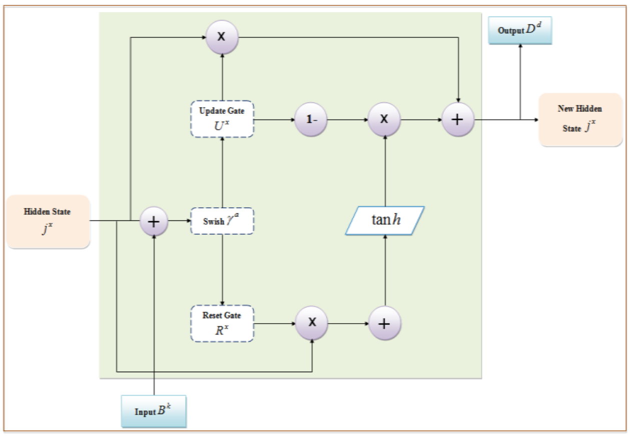

Fig. 2. Structure of proposed S-EGRU

Step 1: Initially, the incoming B^k is multiplied by the weight values (ω), and the previous output (J^{x-1}) and fed into the reset gate through the swish activation function (γ^a). Thus, the reset gate output $(\Re^x)$ is,

$$\Re^{x} = \gamma^{a}\left(\omega \cdot \left(J^{x-1} + B^{k}\right)\right) \qquad \ldots (9)$$

$$\gamma^{a}\left(B^{k}\right) = B^{k} \cdot Sigmoid\left(B^{k}\right) \qquad \ldots (10)$$

Step 2: Afterward, $\Re^{x}$ is fed into the update gate $\left(U^{x}\right)$, where $\Re^{r}$ gets multiplied with J^{x-1}.

$$U^{x} = \gamma^{a}\left(\omega \cdot \left(J^{x-1} + R^{x}\right)\right) \qquad \ldots (11)$$

To produce the final output, U^{x} thus obtained undergoes both element-wise multiplication (ψ) and inverse operation. Hence, the hidden state output $\left(J^{x}\right)$ becomes,

$$J^{x} = \Re^{x} \cdot \left(1 - U^{x}\right) + \psi \qquad \ldots (12)$$

Thus, the data in the current memory content $\left(\hat{J}^{x}\right)$ becomes,

$$\hat{J}^{x} = \tanh\left(\omega \cdot \left(\Re^{x}\right) * J^{x-1} + B^{k}\right) \qquad \ldots (13)$$

The final output obtained at the S-EGRU output gate (J) is,

$$J = \left(1 - U^{x}\right) * J^{x-1} + U^{x} * \hat{J}^{x} \qquad \ldots (14)$$

So, based on the trained attributes, the S-EGRU detects the disease and provides the treatment information to the doctor for giving treatment to the patient. Hence, the l number of diseases detected and the treatment recommended $\left(D^{d}\right)$ is modeled as,

$$D^{d} = D^{1}, D^{2}, \ldots, D^{l} \qquad \ldots (15)$$

The pseudocode of the proposed S-EGRU is displayed below.

```
Pseudocode for proposed S-EGRU
Input: Score value (B^k)
Output: Disease detected and treatment recommended (D^d)
Begin
    Initialize B^k = B^1, B^2,...,B^K
    Initialize weight values (ω)
    For 1 ≤ k ≤ K
        Input B^k to S-EGRU
        Obtain ℜ^x = γ^a(ω·(J^{x-1} + B^k))
        Define Swish activation function (γ^a)
        Compute U^x = γ^a(ω·(J^{x-1} + R^x))
        For each U^x
            Perform ψ and inverse operation
            Update J^x = ℜ^x·(1 − U^x) + ψ
            Evaluate current memory content (Ĵ^x)
            Obtain J = (1 − U^x) * J^{x-1} + U^x * Ĵ^x
        End for
    End for
    Return (D^d)
End
```

Global model training: In the end, for future reference, the entire local model and the attributes extracted get updated into the Global training model.

C.KLD-Diversity-based Privacy preservation

For now, a privacy preservation mechanism is undergone by the attributes extracted. For securing sensitive attributes using a microdata table, L-Diversity is mostly used. KLD is introduced since L-Diversity undergoes a homogenous pattern attack; hence, it is named KLD-Diversity. So, the h well-represented values for E^i using KLD (KLD) are,

$$KLD = \eta(h, E^i) - \eta(h) \qquad \ldots (16)$$

Where, η implies the cross entropy.

D. IPFS

Then, the encrypted data thus obtained is stored in the IPFS. It is a distributed system for storing and accessing patient data.

E. Data accessing

Nowadays, authentication verification takes place using the RDF-tiger method when the doctor wishes to access the patient data from IPFS, as detailed in section 3.5.1. The patient details are downloaded if the hashcode matches the login hash code.

a. RDF-Tiger

A 512-bit block-cipher-based eight 64-bit input and 192-bit output-based cryptographic hashing algorithm is termed tiger hashing. Nevertheless, pseudo-collision is caused by grouping the input into eight 64-bits. Thus, the RDF-Tiger technique is used and is explained below.

Step 1: Here, the attributes obtained from the hospital and patient are fed into the RDF technique as (17),

$$\beta = \left(E^{512}, E^{511}, \ldots, E^{1}\right) \bmod \zeta \qquad \ldots (17)$$

Where, ζ is the reverse function.

Step 2: The input thus obtained is then mapped using the substitution boxes followed by key generation via the key schedule approach. Various stages involved in RDF-Tiger are save, key schedule, and feed-forward, and are elucidated below,

$$\begin{cases} \Gamma_0\Gamma_0 = u^* \\ \Gamma_1\Gamma_1 = v^* \\ \Gamma_2\Gamma_2 = w^* \end{cases} \qquad \ldots (18)$$

$$\begin{cases} in\left(u^*, v^*, w^*\right) \\ f^{1}\left(u^*, v^*, w^*\right) \\ Keyschedule \\ f^{2}\left(u^*, v^*, w^*\right) \\ Keyschedule \\ f^{3}\left(u^*, v^*, w^*\right) \end{cases} \qquad \ldots (19)$$

$$\begin{cases} u^{(1)} \wedge = u^* u^* \\ v^{(1)} - = v^* v^* \\ w^{(1)} + = w^* w^* \end{cases} \qquad \ldots (20)$$

Here, $u^{(1)}, v^{(1)}, w^{(1)}$ implies the obtained 192-bit hash values, $\wedge, +, -$ signifies the XOR, addition, and subtraction operation, f^{1}, f^{2}, f^{3} implies the compression function, and u^{*}, v^{*}, w^{*} stands for the registers. Hence, the hash values obtained using RDF-Tiger $\left(M^{e}\right)$ are represented as,

$$M^{e} = M^{1}, M^{2}, ..., M^{E} \quad \ldots (21)$$

Here, $e = 1,2,...,E$ signifies the E-number of hash values generated.

F. Blockchain server

For further access, the hash values thus obtained are then stored in the blockchain. Blockchain stores information regarding the hash codes generated. Usually, each block contains information like previous and current hash values, Timestamps, and Nonce. Each block is linked to the previous one. Similarly, the complete information about the downloaded data is also stored in the blocks while downloading the data.

IV Results And Discussions

The proposed methodologies' experimental outcomes are analyzed with the traditional algorithms. The experiments were performed in the working platform of PYTHON.

A. Performance analysis of hashing

Here, the Hash-Code Generation (HCG) time proposed RDF-Tiger hashing algorithm is compared with the conventional Tiger, Secure Hashing Algorithm-512 (SHA512), Message Digest-5 (MD5), and SWIFFT hashing techniques.

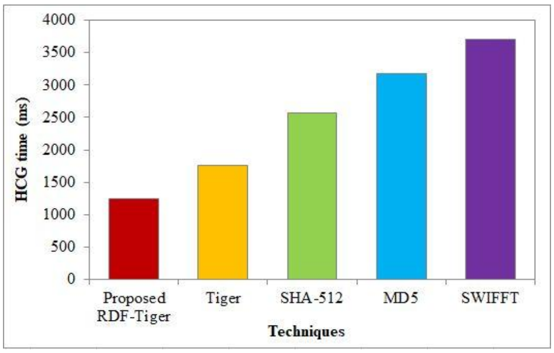

Fig. 3. Experimental results of HCG time

Hash codes are generated in less time of 2164ms with the traditional Tiger hashing technique than the SHA-512, MD%, and SWIFFT techniques, which are given in Figure 3. Nevertheless, the HCG time was

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reduced to 1645ms with RDF involvement. Hence, the RDF-Tiger hashing is the best for hashing in the proposed model.

B. Performance Analysis of Classification

Regarding accuracy, precision, recall, f-measure, and training time, the proposed S-EGRU is analogized to the GRU, Long-Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN).

TABLE 1: TRAINING TIME OF CLASSIFIERS

Techniques	Training time (ms)
Proposed S-EGRU	38232
GRU	43876
LSTM	49348
RNN	55007
CNN	60375

The Training time of the CNN (60375) is higher than the other existing classifiers, which is depicted in Table 1. However, during experimental analysis, the least time (38232ms) taken by the proposed S-EGRU made it to be utilized in the proposed model for classification.

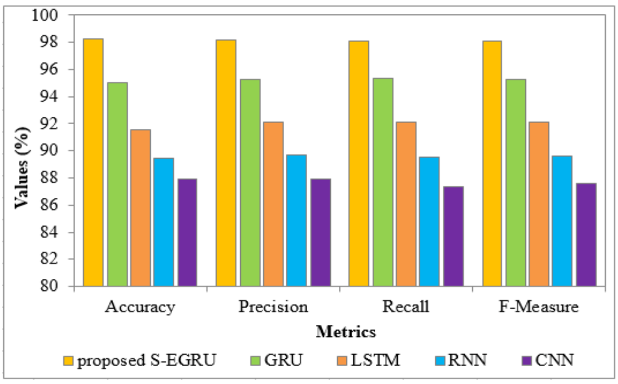

Fig. 4. Experimental evaluation with the performance metrics

Here, the accuracy of the S-EGRU is 3.41%, 7.33%, and 11.80% higher than that of GRU, LSTM, and CNN classifiers. When analogized to conventional classifier algorithms, Figure 4 shown, the proposed S-

EGRU gives better recall, f-measure, and precision results. Hence, the STH and Entropy approach in the GRU makes the proposed S-EGRU as the most reliable classifier for treatment diagnosis.

C. Experimental analysis of privacy preservation

Here, the proposed KLD-Divergence's performance is verified with traditional l-divergence, k-anonymity, and t-closeness results.

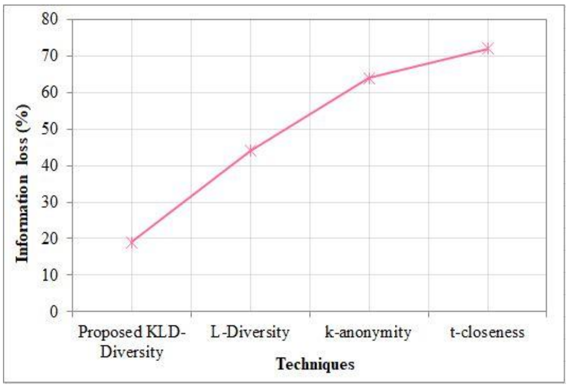

Fig. 5. Information loss with respect to the number of data

As per Figure 5, the information loss of 20% is achieved with the proposed KLD-Diversity technique, which is higher than the compared techniques. More privacy information is preserved with the KLD-Diversity than the other techniques with less information loss.

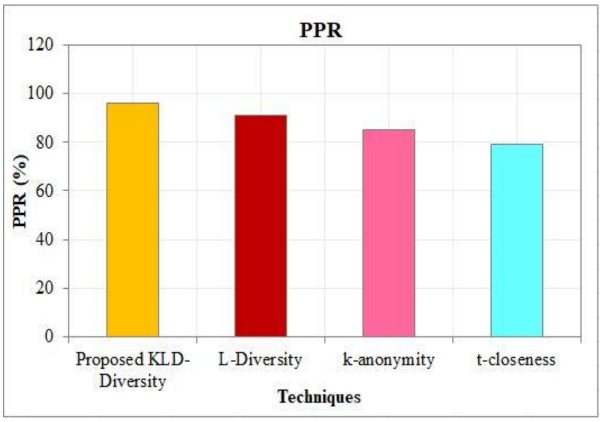

Fig. 6. Experimental results of PPR

A higher PPR of 91% was obtained with the L-Diversity information preserving technique than that of the k-anonymity and k-closeness, which is given in Figure 6. However, the PPR was improved by 4.39% with the KLD involvement in the L-Diversity than the L-Diversity. Hence, higher privacy of the data of the patient can be achieved with the proposed KLD-Diversity.

D. Comparative analysis

Here, the proposed classification models' accuracy is comparatively analyzed with the existing Bi-LSTM [14], Kernel-RF (KeRF) [15] and RF [12].

TABLE 2: COMPARATIVE EVALUATION WITH LITERATURE PAPERS

Techniques	Accuracy (%)
Proposed STH-EGRU	98.28
Bi-LSTM [14]	93
KeRF [15]	98
RF [12]	97.26

As per Table 2, the accuracy level of the proposed classification is 0.28%, 1.04%, and 5.67% higher than the KeRF, RF, and Bi-LSTM techniques. This depicts the reliability of the proposed disease diagnosis and treatment recommendation model.

V CONCLUSION

This paper proposes an FL-DDTRS approach for providing compatible treatment schemes for a disease. The STH-EGRU technique was utilized to suggest disease diagnosis and treatment information to the doctor in FL-DDTRS. For the privacy preservation of patient information, the KLD-Diversity was utilized. In the end, the experimental results of the proposed approaches are analyzed. As per the experimental evaluation, the proposed classifier attained the highest accuracy of 98.28% with less training time of 38232ms with the least information loss. Nevertheless, the usage of IPFS in disease prediction affected the performance by tampering with the intellectual copyright. Thus, the work will be enhanced in the future by using the current data using the hyper ledger blockchain.

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