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An efficient IoT-Artificial Intelligence-based Chronic Kidney Diseases Prediction using Temporal Convolutional Network (TCN) Deep Learning Method in Healthcare System

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ABSTRACT

IOT (Internet of Things) can control the remote based patient's health care monitoring system and here monitoring for the chronic kindney diseases predication levels. When an IoT device collects data from patients, it sends the data to a software application that can be viewed by healthcare professionals and/or patients. Ongoing Chronic Kidney Diseases (CKD) is one of the main supporters of the bleakness and mortality of non-transferable illnesses, influencing 15-20% of the total populace. Early and exact finding of CKD stages is accepted to be fundamental to decrease the effect of unexpected problems on patients, for example, hypertension, sickliness (low blood count), bone mineral issues, poor nourishing wellbeing, and irregularities. Since our requirement is better disease classification for Temporal Convolutional Network (TCN) DL (Deep Learning) methods, the problem of machine learning method is that the existing system cannot detect the level of disease. Our get the Chronic Kidney Disease dataset get from kaggle minimum 1000 and 10000 datas has been used the preprocessing of input datasets. The feature extraction using Latent Dirichlet Allocation (LDA) and this algorithm has been process for specially used for text data or information extraction. This method can be used for perfect extract text data form CKD disease dataset. After extract the data and then approach the classification method of TCN algorithm. In this algorithm to classify the CKD disease level accuracy find out here. Our classification algorithm for TCN examine the extreme performance of pointers being an accuracy.

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1. Introduction

Due to the advancement of Internet of Things (IoT) technology in healthcare, patient care and regular monitoring have significantly improved at a reasonable cost. Various IoT-based medical devices generate large amounts of data, which is automatically transmitted to the cloud for analysis and distribution among stakeholders [1]. Leveraging cloud computing as their primary resource, these devices efficiently collect, analyze, and disseminate information or findings to all involved parties. The volume of data is continuously increasing as more individuals adopt IoT-based healthcare devices on a regular basis.

Chronic Kidney Disease (CKD) is characterized by a gradual accumulation of waste in the body over an extended period. This condition affects people worldwide and can lead to various health issues, including heart disease, diabetes, and hypertension. Age and gender also play a role in CKD risk, alongside these serious health conditions. When kidneys fail to function properly, you may experience symptoms such as back pain, stomach discomfort, diarrhea, fever, nosebleeds, rash, and vomiting. Diabetes and hypertension are common contributors to kidney damage over time; thus, preventing CKD involves managing these conditions. Unfortunately, CKD often remains undetected until it reaches an advanced stage since it typically doesn't present noticeable symptoms in its early phases.

Chronic Kidney Disease (CKD) affects approximately 14% of the global population, and it is characterized by a gradual decline in kidney function over time. While kidney transplants and dialysis are currently saving the lives of millions worldwide, this may only represent 10% of those in need of such interventions. The primary determinant of CKD staging is the glomerular filtration rate (eGFR), which depends on factors like age, gender, race, and creatinine levels. This study addresses the limitations of existing methods for handling missing values in CKD data, proposes a new approach, and compares them using the UCI dataset. Additionally, when making predictions from clinical data associated with CKD, this research emphasizes the importance of statistical analysis and a thorough understanding of the variables involved.

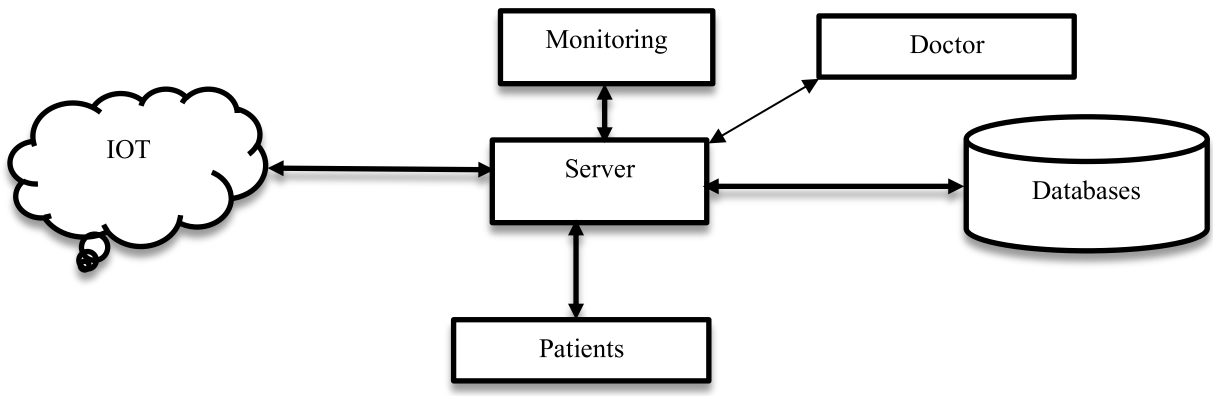

Fig. 1. General Architecture IOT based health care system

Figure 1 illustrates the functioning of the Internet of Things (IoT) in the healthcare system, where it enables simultaneous patient health monitoring. The system centralizes all controls on a server, which interfaces with the IoT cloud, facilitating communication between patients and doctors. This setup ensures efficient communication, allowing doctors to monitor patient health with ease.

2. Related Works

The growth of the Internet of Things (IoT) and the widespread use of small, portable biosensors are creating new possibilities for healthcare monitoring. However, to establish a reliable and flexible healthcare monitoring system, several challenges need to be addressed. This article proposes the incorporation of big data analysis into a healthcare IoT framework [2].

In a study Hussain and colleagues[3], they employed advanced knowledge to predict early-stage CKD and pre-processed the data using neural networks to handle missing variables, achieving an impressive accuracy of 0.995. The researchers eliminated outliers, identified the seven most significant attributes through statistical analysis, and applied principal component analysis (PCA) to reduce dimensionality while preserving key characteristics.

The accuracy of the trained models in the aforementioned study is significantly influenced by the method used to handle missing values. When a neural network with 260 complete data cases for only 20 attributes is used, the accuracy of the missing value estimation is only slightly reduced [4]. However, the accuracy of substituting missing values was notably impacted by the exclusion of attributes with over 20% missing values. It is easier to select attributes for the training set when the source attributes, such as blood tests and urinalyses, are categorized into distinct groups.

The provided data was used to propose a method for predicting the stages of CKD, based on the five CKD phases, achieving an overall accuracy of 0.97 and an overall accuracy of 0.967. Orientation and identity are distinct attributes [5]. Constants were employed to handle missing values in the model, resulting in slightly reduced accuracy. However, their investigation demonstrates that the MCAR technique for small datasets is accurate in randomizing the missing data points [6].

Furthermore, Nair *et al*., [7] established a relationship between serum creatinine and assessed features. However, serum creatinine cannot be utilized in the early stages of CKD since it may exhibit uniform levels, and the combined significance of other parameters does not surpass that of serum creatinine [8-10]. Nevertheless, it proves effective in disease prediction.

When dealing with new events beyond the dataset, it is essential to question the validity of the trained models. In 2017, a team of experts used a multiclass decision tree to predict CKD based on 14 criteria, achieving an accuracy of 0.991 [8]. Subsequently, when employing a neural network and logistic regression model, they removed instances with missing data, resulting in overall accuracies of 0.975 and 0.960, respectively. The selected feature relationships ranged from 0.2 to 0.8. From a clinical perspective, CKD leads to hypertension, which is caused by CKD and has a correlation of 0.73 with the specific gravity category. If these attributes are dropped, the accuracy may be adversely affected [9].

The Guileless Bayes, Multi-facet Discernment, and J48 algorithms exhibit the best Receiver Operating Characteristic (ROC) and ROC 1 precision, achieving accuracies of 0.950, 0.9975, and 0.99, respectively. To assess the effectiveness of the argument, the kappa statistic was utilized, awarding the multi-facet perceptron the highest score of 0.9947, followed by the decision table and J48 algorithms with a score of 0.9786. However, when examining the relevant study using the UCI CKD dataset, several factors, such as missing values and improper treatment of the feature selection approach, need to be highlighted [10].

The Artificial Intelligence algorithms employed in another study [11] included the Support Vector Machine (SVM) classifier, K-Closest Neighbor (KNN) algorithm, Random Forest technique, and Decision Tree algorithm. The training data for these algorithms was sourced from the UCI repository [11]. To enhance the accuracy of CKD prediction, data preprocessing methods are applied to the dataset after training these algorithms.

In another research [12], the proposed approach incorporates the hybrid CatBoost technique, which iteratively adjusts the training pattern weights to provide valuable predictions. This technique is employed to establish an initial linkage factor between the training vector and the test vector for CKD patient data. As the learning rate increases, the accuracy of the predictions improves. Several quantitative metrics, including accuracy, precision, recall, and F1Score, are utilized to validate the effectiveness of the proposed method.

The initial stages of CKD pose a global health risk as they may not manifest noticeable symptoms. To facilitate prompt treatment for patients, machine learning approaches can be developed to identify CKD-causing factors at an early stage. This article aims to predict CKD utilizing various attributes. The data for this study was obtained from a publicly available dataset collected in India [13]. The prevalence of CKD is increasing worldwide, necessitating more advanced detection and diagnosis methods. AI-based models offer the potential for early and accurate predictions. In this study, we employ deep learning models based on AI to predict CKD and non-CKD cases. Additionally, we utilize stacking and voting ensembles of SVM, RF, Adaboost, LDA, and MLP models to achieve precise and efficient CKD and non-CKD event predictions. Performance metrics such as accuracy, precision, recall, F1 score, and ROC were used to assess the effectiveness of the models [14].

Despite advancements in surgery and treatment, CKD remains a significant global health concern. In comparison to existing models, evaluation of the proposed model revealed its ability to predict CKD with 98.5% accuracy and 87.5% sensitivity [15]. The analysis of the findings demonstrates that the utilization of state-of-the-art deep learning algorithms can greatly assist in clinical navigation and aid in the early detection of CKD and related disorders, thereby mitigating the progression of renal damage. CKD is one of the major clinical challenges with a high global mortality rate. In its early stages, CKD presents no symptoms, often leading to delayed diagnoses. Patients with HIV have a higher risk of developing CKD, which can be life-threatening [16]. Considering the increased risk of morbidity and mortality, chronic kidney disease is recognized as a serious health issue. Kidney diseases are difficult to identify due to their slow and persistent nature. Additionally, many individuals do not receive a diagnosis until a late stage as a result.

Evaluating CKD at an early stage requires the use of reliable methods [17]. AI has proven to be an effective approach in various industries, such as stock market predictions or recommending preferred movies. In this study, we harnessed the power of AI and machine learning to develop an application that supports clinical students during their training [18]. To ensure personalized treatment that enhances patients' quality of life and extends lifespan, early identification and prediction of the course of CKD over a specific period are crucial. In this research, we explored how AI and deep learning models can be utilized to predict end-stage renal disease (ESRD) using readily available clinical and lab data from CKD patients [19].

In the present era, chronic kidney disease (CKD) poses a significant challenge, necessitating an accurate diagnosis. The fake minority up-sampling approach demonstrated superiority over the fully featured fake minority up-sampling method for features selected with lower absolute sum and regression operator selection. The oversampling technique of fake minority with selected features exhibits minimal bias and regression operator saturation [20]. The primary objective of this study is to develop Artificial Neural Network (ANN) models for predicting survival in patients with chronic kidney disease. Patients with renal disease gradually lose the essential function of their kidneys to filter blood over time. Survival at the terminal stage requires regular hemodialysis or a kidney transplant [21]. Electronic medical records (EHRs) are revolutionizing healthcare at a rapid pace. Patient clinical history and personal data are digitally stored in an EHR. However, due to security concerns, sharing EHR data with the ML research community to enhance the healthcare system and provide patients with high-quality medical care is restricted [22].

Our selected approach significantly enhances the disease prediction capabilities of neural networks. Moreover, we demonstrate that XGBoost and other transparent, more interpretable classifiers perform equally well as popular deep learning models for disease prediction. Additionally, by conducting a comprehensive analysis of several AI algorithms in disease prediction tasks, our research contributes to the advancement of the current literature [23]. The application of AI in clinical settings is currently a captivating subject for academics. The combination of Artificial Intelligence and Machine Learning not only addresses complex problems but also revolutionizes the medical industry. By integrating all relevant facts and data from various sources and observations, AI aims to continuously improve knowledge over time [24]. The success of the Internet of Things (IoT) paradigm relies on VLSI (Very Large-Scale Integration) architecture that is low cost, low form factor, and extremely energy-efficient [25, 26].

3. Proposed System

The proposed system involves several components, starting with preprocessing and feature extraction using the Latent Dirichlet Allocation (LDA) algorithm. This algorithm helps extract relevant data from the dataset. Subsequently, the classification step employs the deep learning based TCN algorithm to predict and classify the CKD disease levels, and the accuracy of these predictions is measured based on the dataset. The system architecture is illustrated in Figure 2, which provides an explanation of how all these components work together.

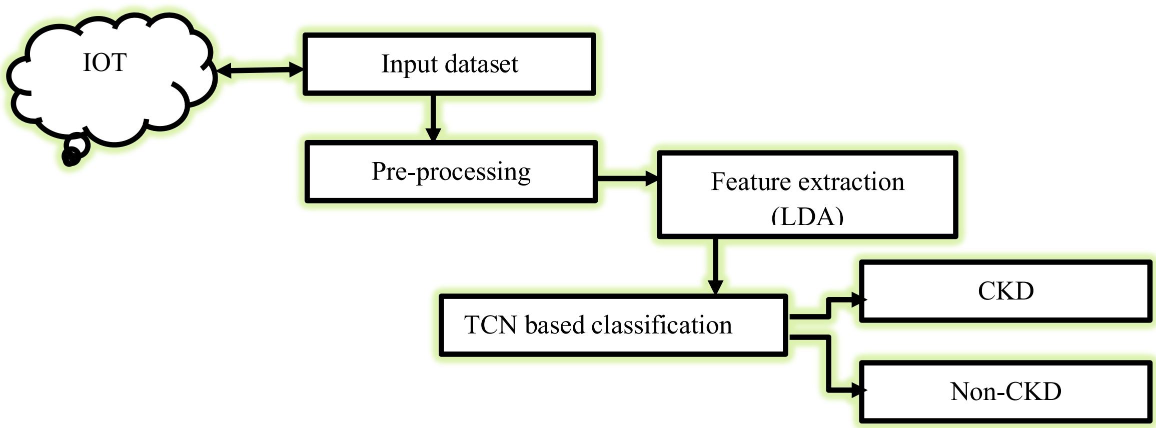

Fig. 2. TCN based Proposed system architecture

A. Pre- Processing

Preprocessing plays a crucial role in predicting CKD disease and involves obtaining data from Kaggle datasets. The input data is derived from collections of CKD disease data and is organized based on various attributes, which are defined in Table 1. In Table 2, a test is performed to detect missing values using the Little's MCAR (Missing Completely At Random) test, where "p" equals zero, indicating that the missing values are entirely random. For the CKD results, if missing values are constants, they are removed to enhance accuracy. Furthermore, the minimum and maximum levels of CKD disease are calculated from the data.

Table 1
The following testing attributes information's

Attribute	Missing percentage	Test to obtain
Class	0.00 %	Doctor's Inspection
Appetite	0.027 %	Doctor's Inspection
Anemia	0.027%	FBC
Hypertension	0.025%	Doctor's Inspection
Diabetes Mellitus	0.50%	FBC
Coronary Artery Disease	0.50%	Doctor's Inspection
Pus Cell Clumps	1.00%	UFR
Bacteria	1.00%	UFR
Blood pressure	4.00%	Doctor's Inspection
Serum creatinine	5.25%	Serum creatinine
Blood Urea	5.75%	BLOOD UREA
Blood Glucose Random	11.00%	RBS
Albumin	11.50%	UFR
Specific Gravity	11.75%	UFR
Sugar	12.25%	UFR
Hemoglobin	14.00%	FBC

Table 2
MCAR test Result

Name	Values
Chi.Square	3167.478
degree of freedom	2245
Freedom P values	0
missing pattern	110

B. Feature extraction

Latent Dirichlet Allocation (LDA) is an unsupervised algorithm used for assignment or extraction. It assigns values to both documents and predefined topics. In LDA, documents are treated as combinations of subjects, and subjects are treated as combinations of words. The algorithm determines the total number of topics, which is then applied repeatedly to each word. Initially, words are randomly assigned to topics, and then the algorithm evaluates which words within a topic the given word appears most frequently.

LDA Algorithm
Step1
Input dataset K
Step2
$for\ all\ topics\ K\ \in [1, K]\ do$
Step3
Mixture text components $\varphi k \sim Dir(\beta)$
Step4
$for\ all\ topics\ m\ \in [1, M]\ do$

Step5
Text mixture proportion $v_m \sim Dir(\beta)$

Step6
$for\ all\ text\ topics\ n\ \in [1, N_m]\ in\ text\ \ m\ do$
Step7
Text topic index $Z_{m,n} Multinomial(v_m)$
Step8
X =Term text $W_{m,n} Multinomial(\varphi_{m,n})$
Step9
Return X
Here
M is the no of text corpus
K is the mixture the text components
V is the Vocabulary
N is the number of text corpus
$v_m\ mixture\ components\ for\ each\ \ topic\ or\ text$
$\varphi k\ \ one\ proportion\ of\ ecah\ text$
$N_m\ is\ length\ of\ the\ text$
$Z_{m,n}\ choice\ the\ text\ topics$
$W_{m,n}$ nth of the text components

The algorithm does not possess any topic information. Instead, it computes the hidden structure of observed documents, leading to the generation of an inferred topic distribution. To tackle the task of inferring proportions of latent themes, it becomes essential to calculate the posterior distribution of the latent variables described in the literature.

C. TCN Classification

During the training phase, considerations were made for the classification model. A comparison was drawn between the SVM (Support Vector Machine) neural network and the Long Short-Term Memory Networks (LSTMs) regression with the TCN model. The dataset was split into three sections: 70% for training, 15% for cross-validation, and 15% for testing, with random division. Deep learning algorithms are adept at handling large volumes of text data from datasets. The Multilayer Perceptron (MLP) can easily classify both nonlinear and linear data. By utilizing multiple layers, the MLP method can identify text patterns and effectively handle batch data extraction. Our approach employs a 5x5 layer structure for the MLP method, with the input layer, hidden layer, and output layers used to process and hide the data.

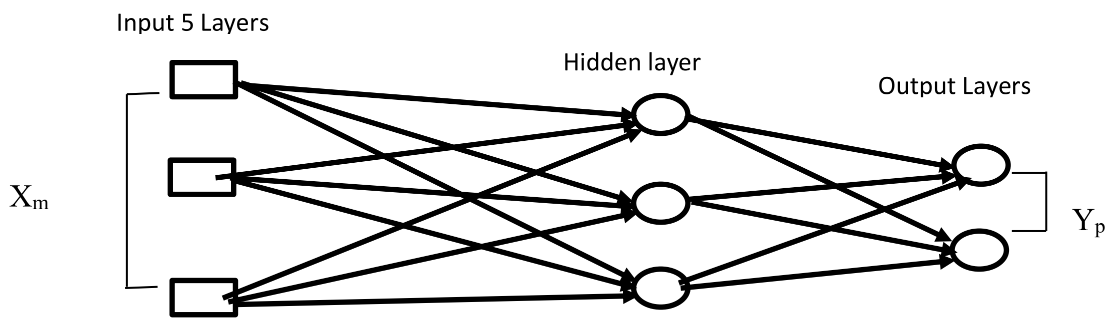

Fig. 3. MLP architecture for TCN with 5 layers

Figure 3 illustrates the architecture of the Multilayer Perceptron (MLP) with 5x5 layers, denoted as X_m for input layers and Ym for output layers. The term "5 layers" corresponds to a 5x5 matrix that is used for text pattern matching, as explained in Figure 4. In this matrix, text pattern matches are checked based on row and column interactions.

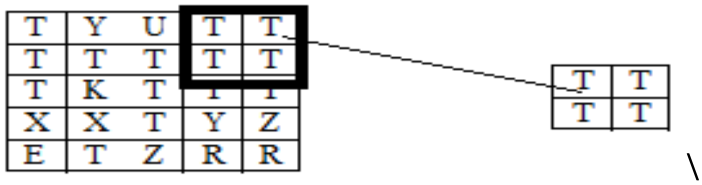

Fig. 4. Example of Text Pattern System

D. Text Classification using TCN

Convolution plays a vital role in the neural network domain, especially in text pattern matching. The input classification involves word IDs W $_{(1,n)}$= W_1..... W_n. An information vector or lattice with dimension d is compared to information representations through a convolutional channel or part of size k, applied to the entire input text. Each bit value is enhanced by the vector, and the resulting values are aggregated. This process employs a direction and weight vector u to embed input vectors within a specified window, followed by a nonlinear activation function g.

Considering a window of word W $_{(1,n)}$= W_1..... $W_{(i+k)}$ the concatenated vector of the i^{th} window is then:

$$W = [\mathrm{W}\ (1, \mathrm{n}) =\ \mathrm{W1} \ldots\ldots + \mathrm{k}] \epsilon R^{k*d} \quad (1)$$

The convolution filter is applied to each window, result in scalar values r_i, each for the i^{th} window:

$$r_i = g(x_i, u) \epsilon R \quad (2)$$

In practice one typically applies more filters, u_1..... u_n, which can then be represented as a vector multiplied by a matrix U and with an addition of term b:

$$r_i = g(x_i . U + b) \quad (3)$$

With $r_i \in R^l, x_i \in R^{(k*d)}, U \in R^{(k,d*l)}\ and\ b \in R^l$

The text processing method is based on a multi-channel approach. In this system, each channel serves a distinct purpose, such as one channel being a sequence of words, another channel being a sequence of related POS (Part of Speech) tags, and a third channel being a pattern of words within a specific window of text or phrase.

After applying convolution to the words or text, an m-vector w is obtained. Similarly, applying convolution to POS tags produces m equal vectors representing the shape, leading to m vectors once more.

$$P_i = words_{l:m} + Shape_{l:m} \quad (4)$$

Or by concatenation

$$P_i = [words_{l:m} + POS_{l:m} + Shape_{l:m}] \tag{5}$$

The purpose of this function is to combine the outcomes of vectors obtained from various convolution windows into a unified vector with a dimension of L.

4. Result and Discussion

The proposed system aims to analyze the CKD dataset and perform classification using the TCN algorithm. In comparison to various algorithms such as Long Term Memory Networks (LSTM) regression and SVM (Support Vector Machine) neural network, the Temporal Convolutional Network (TCN) demonstrates superior performance in classification. The experimental analysis is conducted using Python, with a maximum word or text size of 19000. The evaluation of results is carried out using a deep learning-based TCN algorithm, and a multilayer approach is employed for classification. Table 1 illustrates the training dataset's loss accuracy for TCN classification, with values and performance recorded for each Epoch.

Table 3 displays the testing dataset's loss accuracy for TCN classification, presenting the values and performance achieved for each Epoch.

Figure 5 illustrates the chart of training dataset loss accuracy, comparing various limitations from 1 to 10 Epochs. In Round-1, the loss accuracy at the Epoch is recorded as 0.6664, and in Round-2, it is 0.4823. The training dataset's loss accuracy continues to improve until the final Epoch, reaching a value of 0.0276.

Table 3
Experiment Result for training dataset loss accuracy

Epoch	Loss accuracy
1	0.6664
2	0.4823
3	0.3224
4	0.2039
5	0.125
6	0.0943
7	0.0579
8	0.0578
9	0.0285
10	0.0276

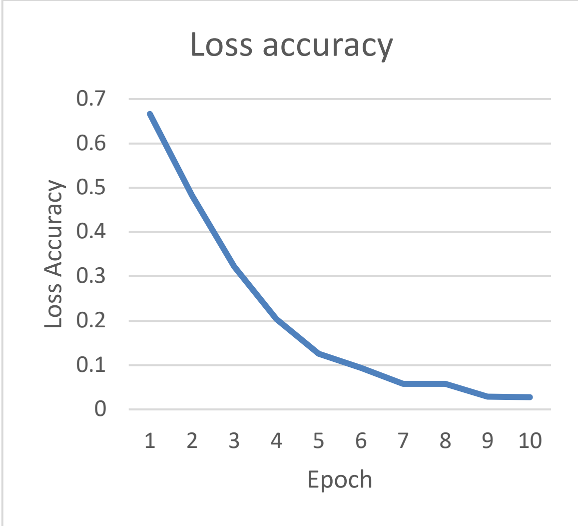

Fig. 5. Training Dataset Loss Accuracy

Table 4
Experiment Result for testing dataset validation accuracy

Epoch	accuracy
1	0.5628
2	0.7668
3	0.8789
4	0.8545
5	0.8657
6	0.9431
7	0.9694
8	0.9788
9	0.9797
10	0.9908

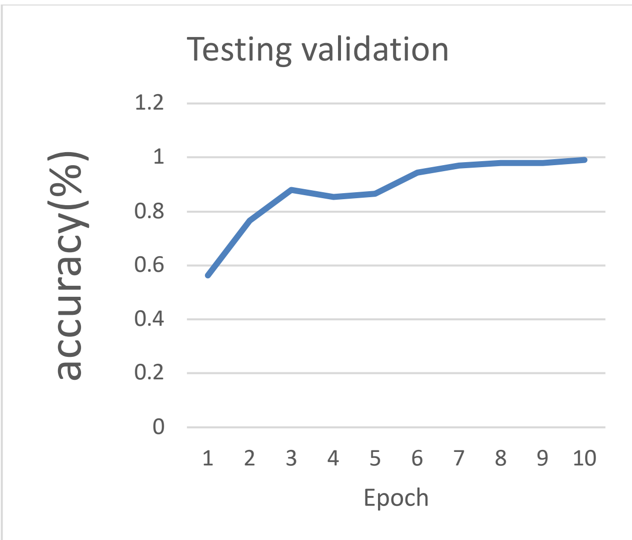

Fig. 6. Testing validation Accuracy

Figure 6 presents the chart of testing validation accuracy, comparing various limitations from 1 to 10 Epochs. In Round-1, the accuracy value at the Epoch is recorded as 0.5628, and in Round-2, it is 0.7668. The testing validation accuracy continues to improve until the final Epoch, reaching a value of 0.9797.

Table 5
Experiment Result for TCN Performance

Methods	Performance (%)
LSTMs	94.5
SVM	95.5
TCN	98.5

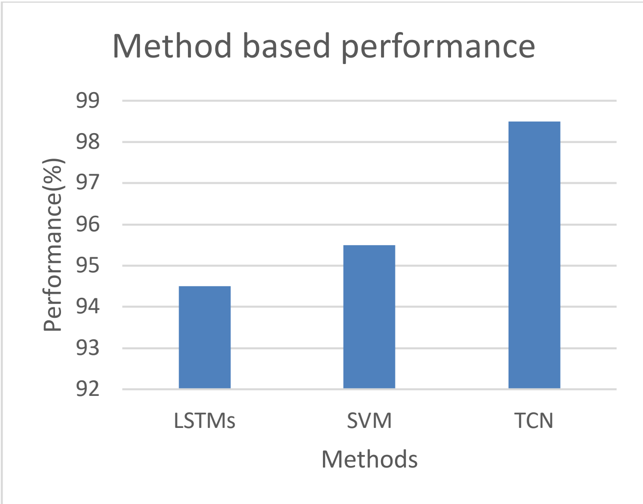

Fig. 7. Experiment Result for TCN Performance

Figure 7 illustrates the classification performance chart, comparing various algorithms. LSTMs achieve a performance of 94.5%, SVM achieves 95.5%, and TCN achieves 98.5%. Ultimately, TCN exhibits the best performance among the algorithms for classification.

5. Conclusion

The proposed system focuses on predicting CKD Disease using an Internet of Things (IoT) framework, utilizing the TCN-based deep learning algorithm for classification. For text extraction from the dataset, the LDA algorithm was employed, effectively filtering linear or nonlinear text or words. The TCN algorithm with MLP-based layer formations and multilayer support was then used for text matching patterns. The classification is based on identifying whether CKD is present or not within the dataset. The CKD dataset was analyzed, and classification was carried out using the TCN algorithm. The performance of the current methods was compared with various algorithms, with Long Short-Term Memory Networks (LSTMs) regression achieving a prediction performance of 94.5%, SVM algorithm achieving 96.5%, and Temporal Convolutional Network (TCN) achieving a prediction performance of 98.5%. Finally, the CKD disease prediction performance proved to be better, providing more accurate results.

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