International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.7081
Article Received: 10 March 2023 Revised: 28 April 2023 Accepted: 20 May 2023

A Novel IoT-based Framework for Urine Infection Detection and Prediction using Ensemble Bagging Decision Tree Classifier

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Abstract—One of the most common conditions treated in adult primary care medicine is Urinary Tract Infection (UTI), which accounts for a sizeable portion of antibiotic prescriptions. A high degree of diagnostic accuracy is necessary because this issue is so prevalent and important in everyday clinical practice. Particularly in light of the rising prevalence of antibiotic resistance, excessive antibiotic prescriptions should be avoided. To examine the machine learning approach and Internet of Things (IoT) for urinary tract infections, this research proposes an Ensemble Bagging Decision Tree Classifier (EBDTC). In our study, to learn more about UTI, we conducted a study in which we collected the physiological data of 399 patients and preprocessed them using the min-max scalar normalization. Feature extraction using Principle Component Analysis (PCA) and classification using Ensemble Bagging Decision Tree Classifier (EBDTC). The performance outcomes of accuracy (96.25%), precision(96.22%), recall (98.07%), and f-1 measure(97.17%) demonstrate the proposed strategy's significantly improved performance in comparison to other baseline existing techniques.

Keywords-Urinary Tract Infection (UTI), Internet of Things (IoT), min-max scalar normalization, Principle Component Analysis (PCA), Ensemble Bagging Decision Tree Classifier (EBDTC).

I. INTRODUCTION

Infections of the urinary tract are more common after respiratory tract infections experienced in humans. The number of requests for bacteriuria diagnosis, nevertheless, far exceeds that for microbial infections [1]. There is no need to seek medical attention because the vast majority of upper respiratory infections are caused by viruses and display only mild symptoms. Urinary tract infections, on the other hand, are almost always caused by bacteria and require treatment with antimicrobial medication to eliminate the infectious agents. Symptomatic infections as well as those that are asymptomatic carry the risk of serious consequences if they are not treated [2]. The pathogens vary in their severity from a solitary, moderately merely a symptom primary infection caused by a pathogen like Escherichia coli that may heal on its own to a much more significant repeating infectious disease like chronic pyelonephritis that could be caused by resistant organisms that are frequently challenging to treat [3]. Figure 1 indicates the Urinary Tract Infection.

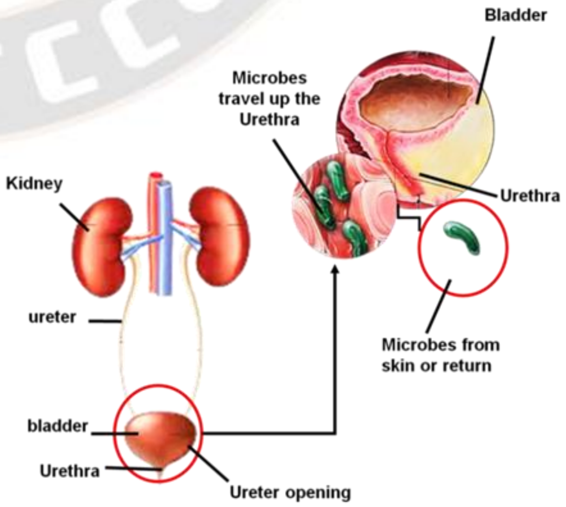

Figure 1: Urinary Tract Infection

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The infections can also be brought on by organisms that are not susceptible to the treatment that is being administered [4]. Symptoms of a UTI include a burning feeling while urinating, the urge to urinate commonly, discomfort in the lower back or abdominal muscles, urine that is overcast, gloomy, and starts to smell strange, in addition to a fever and chills. Another symptom of a UTI is an increase in the amount of urine that is passed. As a standard practice, urologists advise patients to drink copious amounts of water in addition to taking antibiotics and pain medication [5]. Managing UTIs also includes good hygiene, such as washing your hands from front to back after using the restroom. By reasoning about knowledge and also by employing a variety of learning strategies, many researchers have developed expert systems intending to solve difficult diagnostic problems in the medical field, such as cancer diagnosis and the diagnosis of acute inflammation in the urinary system, amongst others [6].

The Internet of Things is analogous to a method for connecting computers, digital and mechanical machines, things, or humans with using the one of a kind system and avoiding any data transmission via an able human-to-human or computer-to-computer relation. Similarly to how humans and computers can share and receive data from one another over the internet, IoT devices may also be given their own unique internet protocol addresses and communicate with one another and other devices via the network [7]. The Internet of Things (IoT) and other forms of smart technology are developing rapidly, opening up new opportunities for improving many aspects of modern living. IoT technologies aim to streamline operations across industries, boost the effectiveness of existing infrastructures (whether they be technological or procedural in nature), and ultimately enhance people's daily lives [8].

To make early predictions of urine infections, we currently propose an Ensemble Bagging Decision Tree Classifier (EBDTC) framework that gathers information about urine and analyses it in real time. The following is a list of the proposed framework's main contributions:

- To introduce a novel IoT-based machine learning solution for the prediction of UTI.
- By using min-max normalization, the correlations between the original data values are retained. This constrained variety will lead to lower degrees of separation that can decrease the impact of outliers.
- PCA reduces dimensionality without sacrificing any feature information. Accelerate the learning algorithm. Address the issue of multicollinearity. Assist in the visualization of high-dimensional data.
- Implementing an EBDTC framework that includes results of urine infection predictions.
- Experimental evaluation of the suggested framework to assess its performance in a simulated setting.

The remaining part of this research is divided into 4 sections, section 2: literature survey, section 3: methodology, section 4: result and discussion, and section 5- conclusion.

II. LITERATURE BACKGROUND

The relevant study that employs UTI detection and prediction to collect information for condition management or to avert hazardous health issues is reviewed in this part.

In the research [13], the capacity to categorize UTI groups was essential since the objective was to determine the best screening tool for UTI assessment. Given the amount of raw data required for protein biomarkers, the capacity to deal with high-dimensional records was an essential consideration when choosing methods for machine learning. In RF, trees are now the only design necessary on a comparatively tiny subset of characteristics rather than all characteristics at each split, which makes it an excellent candidate algorithm for resistance to high. As the separate hyperplane for SVMs does not rely entirely on the support vectors for data, it has independent advantages when handling high-dimensional data.

Machine learning techniques are used on clinical electronic health record data to predict the possibility of susceptibility to both first-line and second-line antibiotic treatments for UTIs [14]. The proposed decision algorithm can recommend the antibiotic to which an individual is susceptible. It maintains the optimal treatment by increasing the reductions in the use of broad-spectrum antibiotics.

A study [15] demonstrates the effectiveness of machine learning techniques in detecting and predicting the need for a bacterial culture of urine samples. Due to the increased demand caused by an aging population in most industrialized and emerging nations, drastic change is needed to improve economic viability and capability in laboratory testing. It shows a reduction in culture workload by 41%.

In the paper[16], a framework is developed which collects the data and performs an intensive study on the observations received to build a machine-learning model. This developed platform analyzes the risk associated with UTI. The machine learning model provides 83% precision and 91% recall in detecting and predicting UTI risks.

The study [17], discusses monitoring dementia patients' health and well-being by combining the IoT and in-home sensory devices with machine learning. They will be able to provide better treatment as a result, that is preventative and much less likely to lead to needless hospital admissions. UTI is one of the top five causes of hospital admissions for persons with

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dementia, and they have created an algorithm to help with it. To build the UTI detection method, non-negative matrix prime factorization (NMF) is used to extract latent components from raw observations, cluster them, and identify probable UTI cases.

The study [18] establishes the foundation for an Internet of Things-based smart toilet system that, among other things, makes it possible to make an accurate diagnosis of urinary tract infection (UTI) at home. The data for this study came from electronic healthcare records, and it was supplemented with an examination of secondary data derived from a case-control study.

The purpose of [19] was to characterize a deep learning and information retrieval strategy that was employed to discover data regarding catheter-associated UTI from a wide range of sources, such as electronic healthcare records and nursing workload data. It helps in providing the required pieces of evidence to the nursing staff for practice.

The aim of [20] was to develop a computer-based risk evaluation system for catheter-associated UTI and evaluate its validity in terms of making accurate predictions. It helps in the allocation of nursing professionals' efforts and time for the risk associated with catheter-associated UTIs.

The goal of [21] is to examine the performance of k-nearest neighbor and SVM with a difference in the distances and achieve a considerable diagnosis regarding the urinary system. The study shows that Support vector machines help identify the infected person.

In the research[22] biomarkers are used to develop a machine-learning-based model for the early detection and prediction of urosepsis. It uses the Gini ranking method for variable filtering. The result of the model shows that the ANN has the highest accuracy of 92.9%.

The paper[23] uses the framework based on Iot-fog computing that uses the XGBoost algorithm to detect and predict UTIs. The developed model gives an accuracy of 91.45% which shows a remarkable improvement in comparison with the baseline techniques,

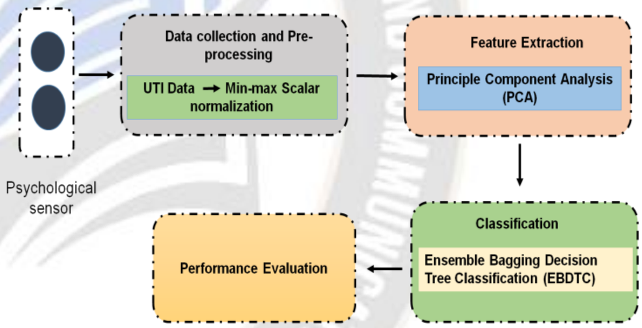
III. PROPOSED METHODOLOGY

The Internet of Things (IoT) has the potential to bring about significant change in the healthcare industry. The healthcare business is transforming as a result of this, as it is enhancing efficiency, cutting costs, and refocusing attention on providing superior care to patients. [24]

In today's world, with the development of the IoT, all entities are connected via some form of communication. The Internet of Things for hospital equipment will provide data that can have a significant impact on both equipment efficiency and patient health.

The Internet of Things (IoT) is being more acknowledged by industry and various services, particularly in the healthcare sector. Medical gadgets based on the Internet of Things (IoT) are currently spreading rapidly, and many different types of health monitoring systems have been developed due to their integration with mobile computing and Information and Communication Technologies (ICT). Massive data sets produced by medical equipment and wireless sensors built on the Internet of Things also present significant prospects for data processing as well as monitoring of patients remotely. Analyzing the state of the art in massive amounts of data and Internet of Things enabled technologies for intelligent settings. Integrating big data into smart settings (such as healthcare and related fields) was also discussed, along with some of the important difficulties, applications, trends, and ongoing research in this area [25].

To detect and predict Urinary Tract Infection (UTI), we implemented an Ensemble Bagging Decision Tree Classifier (EBDTC) in our work and analyzed it with an existing model. Here is a discussion of these techniques. Figure 2 represents the methodology used in this research.



A. Data collection and preprocessing

In this article, we discuss the use of machine learning and IoT technologies to diagnose UTIs. To learn more about a UTI, we conducted a study in which we collected the physiological data of 399 patients. To more easily manage the data for each data, normalization is performed to lessen the negative effects of irregular sample data and to confine the resultant data to a specified range. The following equation (1) is used for determining the level of normality:

$$A' = \frac{a - \min(a)}{\max(a) - \min(a)}, \tag{1}$$

When the beat spectrum computation yields an amplitude value A, normalizing it to a lower value A' yields the normalized value A'.

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B. Feature selection using Principle Component Analysis (PCA)

An ML classifier may fail or converge slowly as a result of redundant and irrelevant features. The PCA technique also referred to as the eigenvector regression filter or the Karhunen-Loeve transform is used in this study to reduce the dimensionality of the raw feature data collected by the Internet of things (IoT) while maintaining the maximum data variance by zeroing out one or more of the weakest principal components. An orthogonal, linear projection operation is used to achieve the dimensionality reduction process. In a broad sense, the PCA operation can be described as

$$Y = XC \qquad (2)$$

The major parts of the projecting given dataset of$X$with$P \leq N$ projections are denoted by $Y \in \mathbb{R}^{S \times P}$. Finding the projection matrix$C \in \mathbb{R}^{N \times P}$) is the same as finding the eigenvalues of the correlation matrix of X, which is the goal of solving a singular value decomposition (SVD) issue for X.

$$X = U\Sigma V^T \qquad (3)$$

In this case, is a linear combination with singular values, and, λ_n, for $n = 0, \ldots N-1$, no increasingly lying along the diagonal. $U \in \mathbb{R}^{S \times S}$and $V \in \mathbb{R}^{N \times N}$perpendicular matrices, in the columns and row directions, respectively. A projections matrices C can be constructed with the first P components of V,

$$V = [v_1, \ldots, v_N] \qquad (4)$$

and

$$C = [c_1, \ldots, c_P] \qquad (5)$$

Where $v_n \in \mathbb{R}^{N \times 1}$ is the right singular vector of X, and $c_n = v_n$.

Where Σ, are the primary axes of the region covered by the columns of C have standard deviations of X, which are denoted by. It is generally accepted that variance is a measure of how much information each variable contributes to a model. To illustrate this, let's take a look at the components where placed variance ratio of the primary components.

$$R_{cev} = \frac{\sum_{n=1}^{P} \lambda_n^2}{\sum_{n=1}^{N} \lambda_n^2} \qquad (6)$$

As a result, λ_n^2 becomes the variance of the X projection in the direction of the nth principal component.

C. Ensemble Bagging Decision Tree Classifier (EBDTC)

TheTo increase predictive performance, ensemble methods employ multiple decision trees as opposed to just one. Bagging and boosting are the two methods with ensemble models that are used the most frequently. For quantitative classification or regression, bagging helps machine learning algorithms achieve higher consistency and accuracy. Reducing variance without losing a decision tree's bias or succumbing to overfitting is what bagging is all about.[26]

To generate a large data set, the Bagging Tree randomly replaces training samples with fresh ones using IoT for detecting UTIs. After deciding on a subset of data to use, the corresponding trees can be trained and used to inform the development of models. The average of all the predictions made by these trees is then used to make the final choice more securely. A single tree's accuracy can be increased by using numerous copies of the training subset of Iot.

In circumstances with high bias, boosting is a helpful ensemble technique. Simple training models are used to train the predictors sequentially, after which the data is examined for errors. The prior decision tree is used to calculate the net error at each step. When an input in a high-bias dataset cannot be accurately classified by one hypothesis, its weight is increased in hopes that the subsequent hypothesis will do so.

On a set of inputs that were accurately classified and had little bias, we used the EBDTC for the current study. The learning process is more effective because the method produces results with less variance than its components.

The training dataset determines the most effective classifier type. We used a classifier in the current study that offers the best memory, speed, interpretability, and flexibility trade-off.

To create an algorithm of continuous classifiers, we first split the dataset into two possible categories (Hm,=1 … MHm,=1 … M). For a given training set D, we have Hm: Dm → RHm: Dm → R. The created classifiers were then combined into a single classifier, and the prediction weight was calculated as follows:

$$H(d_i) = \operatorname{sign}\left(\sum_{m=1}^{M} a_m H_M(d_i)\right), \text{where sign is ; sign } (x) = \begin{cases} 1, x > 0 \\ 0, x = 0 \\ -1, x < 0 \end{cases} \qquad (7)$$

For each classifier, Equation (7) provides a voting mechanism known as majority (plurality) voting. Plurality voting effectively reaches the best compromise between error and rejection. The majority of classifier votes determine how an example di is labeled. These parameters am, m=1,..., M, show how much better classifiers affect the end outcome. Due to their superior accuracy over purely random classifiers, Hm is categorized as a "weak classifier". In our study, we applied the ensuing EBDTC in algorithm 1.

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Algorithm 1: EBDTC

Input: a matrix of variables and the category score for every training

Output: the W-vector of estimates of the variables' quality

1. Set W[A] =0.0 for all values.

2. I=1 to m do start

3. Choose an instance at randomly R_i;

4. Construct node N;

5. Tuples in D must all belong to the same class, C, otherwise.

N will be given back as a leaf node with the category C label;

6. Whenever the attribute _list is null,

Return N as D's majority class leaf node; / majority voting:

7. Attribute selection method(D, attribute list) finds the "best" splitting criterion;

8. Splitting criterion node N;

The split feature is precise and There is no restriction on multi-way splits or binary trees.

9. Splitting attributes in the attribute list; delete dividing attribute

10. Split the tuple and construct sub-trees for each division for each result j of the splitting criteria

11. Allow D_j to be the collection of data tuples in D that meet result j;/ a partition.

12. If D_j is empty then

Connect a leaf to node N bearing the majority class's label;

13. If not, join the node that Generates the decision tree(D_j attribute list) returned to

node N;

$$W[A]; W[A] \sum_{j=1}^{k} \text{diff} \frac{A, R_i, H_j}{m.k} \sum_{c \neq \text{class}(R_i..i} [\frac{P(C)}{1 - P(\text{class}(R_i))}]$$

$$\sum_{j=}^{k} \text{diff}(A, R_i, M_j(C))) \ (m.k);$$

14. End

IV. RESULTS AND DISCUSSION

The technique that the "Internet of things (IoT)" was given resulted in an improvement in performance for all of the algorithms that were utilized in this study. In this section, we assess and contrast the performances of the Ensemble Bagging Decision Tree Classifier (EBDTC) for UTI prediction models and Python can be used to simulate. Accuracy, precision, recall, and f1-score are compared to existing methods such as k-Nearest Neighbours(KNN), Artificial Neural network, and XGBoost algorithm. Table 1 illustrates the numerical outcomes.

TABLE I. NUMERICAL OUTCOMES

Methods	Accuracy	Precision	Recall	F1-measure
SVM+KNN	83.5	81	89	83
ANN	89.11	89	81	87
XGBoost Algorithm	92	94	85	95
Proposed (EBDTC)	96.25	96.22	98.07	97.14

A. *Accuracy*

A measure of accuracy is the proportion of correctly classified instances to all instances in the dataset. The mathematical expression for the accuracy measure is:

$$\text{Accuracy} = \frac{X+Y}{Y+X+Z+Q} \quad (8)$$

X = True positive

Y = True negative

Z = False positive

Q = False negative

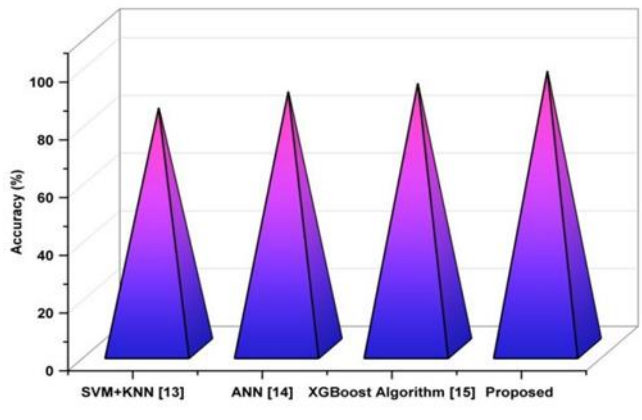

Figure 3: Accuracy

The accuracy for suggested and current approaches is shown in Figure 3. When compared to the current methods, the proposed methods are more accurate.

B. *Precision*

It specifies the percentage of data points classified as infected that are infected. In Figure 4 we see the precision of both the proposed and existing methods. The proposed methods have greater precision than the current methods.

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$$\text{Precision} = \frac{X}{X+Z} \tag{9}$$

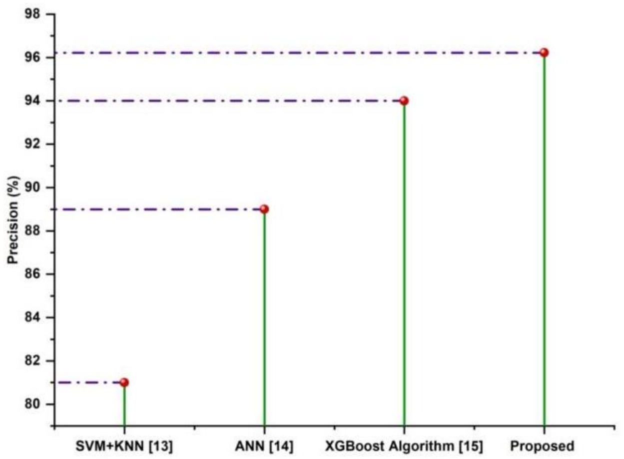

Figure 4: Precision

C. Recall

Correctly identifying a positive test (recall) is defined as the percentage of samples labeled as positive that was labeled as positive. The accuracy with which the model can recognize Positive samples is measured by the recall. Recall increases when more positive samples are identified. The recall of the proposed and existing approaches is shown in Figure 5. The proposed methods outperform the state-of-the-art techniques in terms of recall.

$$\text{Recall} = \frac{X}{X+Q} \tag{10}$$

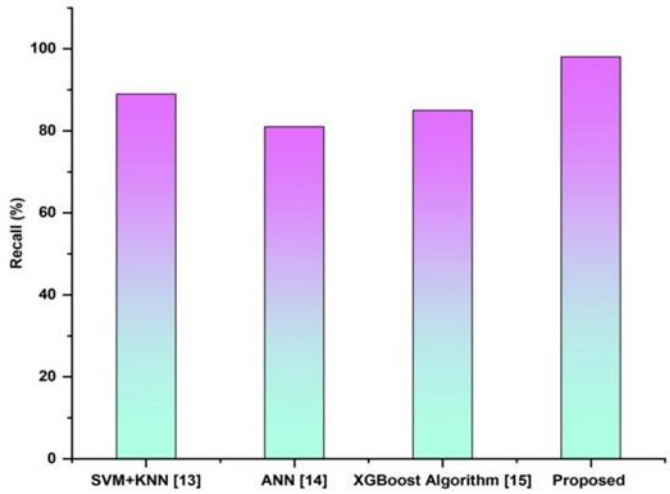

Figure 5: Recall

D. F1- measure

The F1-measure is calculated using the precision and recall results from data analytics, and the mathematical formula is given in the equation below.

$$\text{F1} - \text{measure} = \frac{2 \times P \times R}{P+R} \tag{11}$$

P = Precision

R = Recall

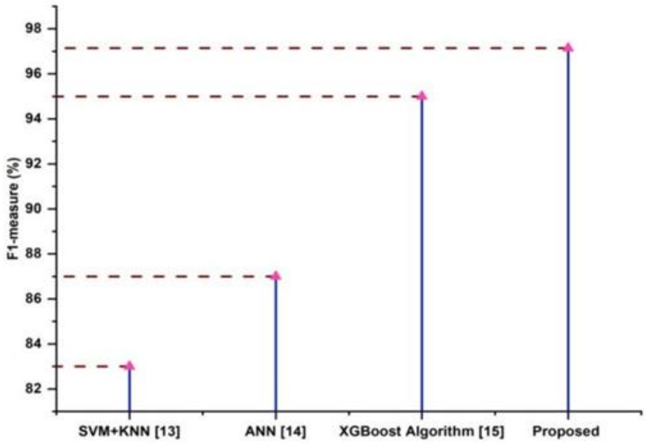

Figure 6: F1-measure

The f1-measure is shown in Figure 6 for both new and established approaches. When compared to conventional techniques, the f1-measure is higher in the new approaches proposed.

V. DISCUSSION

To diagnose acute inflammation of the urinary system, Support Vector Machines and K-nearest Neighbor are used [17]. It performed less well in terms of classification time and had less significant results when dealing with an accuracy rate of 100%. The experiment demonstrated that the suggested diagnosis SVMs may not be as accurate in locating the infected person. Compared to all of the others, the performance of the ANN was the least. When an ANN model was used that included the eight biomarkers with the lowest influence ranking, the model's prediction accuracy was poor.

The XGBoost model, which is used to predict urine infections, is amenable to optimization, which can result in mildly improved performance. As a result, a method of cross-validation that is 10 times more stringent has been used for training. The model is trained on all of the data that is available through the utilization of the 10-fold cross-validation method. In addition to this, this also has the effect of minimizing the bias, which in turn causes the problem of overfitting [19].

To avoid the existing challenges, we proposed a novel Ensemble Bagging Decision Tree Classifier (EBDTC) that has a 96.25% accuracy rate.

VI. CONCLUSION

One of the most common health problems in contemporary society is urinary tract infections. UTI are increasingly more common as a result of our rapidly changing way of life. By utilizing the capabilities of the IoT in machine learning and we have proposed the EBDTC framework for the early detection and prognosis of urinary tract infections.

The Internet of Things has been used to collect data, which was then analyzed at the psychological sensors. Data collected by several sensors are initially preprocessed using min-max normalization. Using patient data, the proposed framework built on the EBDTC has been thoroughly tested. The accuracy, precision, recall, and f-score statistical results, which average 96.25%, 96.22%, 98.07%, and 97.14% respectively, demonstrate the efficacy of the suggested methodology for early urine infection prediction.

Additionally, the proposed methodology's classification time supports its application in real-world scenarios. In the future, a variety of swarm methods that are described in the literature can be used to evaluate the validity of the suggested approach [27][28]. Another issue for further investigation in future research is the security of collected data and the effective storage of predicted results in the cloud against unauthorized access [29][30].

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