

# RECENT DETECTION AND PREDICTION METHODS FOR URINARY TRACT INFECTION IN HUMANS: A DETAILED REVIEW

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## ABSTRACT

Urinary tract infection (UTI) is common infection in humans due to several reasons. It occurs with the incursion and growth of wide range microorganisms, consists of bacteria such as Gram-negative, Gram-positive and fungi. The urinary system consists of kidneys, urethra, ureters and bladder which get affected by urinary tract infection. Primarily the infection occurs in the lower tract of the urinary system i.e. bladder and urethra. UTI get severe, if it appears in upper tract which includes kidneys and ureters. UTI is among a most prevalent diagnosed infection that affects both men and women and it is more common in women because of their physiology. UTI give rise to several diseases related to liver, kidneys and bladder if it left untreated. In the last few years, numerous healthcare devices have emerged which permits people to detect and manage their health conditions easily at home. The aim of this paper is to review and assess the causes, impacts, requirements for the prediction of urinary illness. Urine infection (UI) is the highly common disease in the world's population. UI monitoring has been an issue of concern for healthcare industry. Outcomes are equated by several state-of-the-art forecast methods that shows the reviewed method attain major improvement and high efficacy. Internet of Things enhanced responses in terms of efficiency classification, forecast productivity, temporal delay and stability.

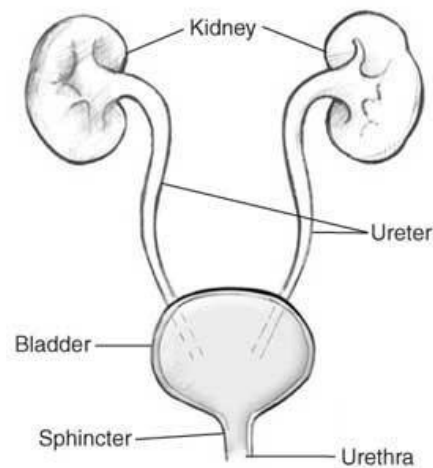
**Keywords:** urinary tract infection (UTI); IoT; artificial neural network (ANN); recurrent neural network (RNN).

## 1. Introduction

Information and communication technology (ICT) innovations have become an important support for providing effective solutions in a variety of industries, including healthcare, logistics and agriculture [1]. Furthermore, with the Internet of Things as a primary driving force for ICT advancements, the healthcare industry manages optimal resource utilisation and provides pervasive healthcare services [2, 3].

Urine infection is one of the most prevalent diagnosed infections. It is related to a variety of bladder, kidney, and liver disorders. Every year, UI affects more than 150 million individuals worldwide [4]. In addition, the WHO released a review study showing that there are over 1 million hospitalizations in the United States in 2011. Global health investment is projected to reach \$8.7 trillion by 2020, owing to rising global population, disease vulnerability and the mobile healthcare business [5]. Urinary Infection is linked to several disorders that can cause serious health problems or even loss of life.

The anatomy of the urinary system as shown in figure 1 consists of renal pelvis, kidneys, bladder, ureters, and urethra. The urinary system and kidneys help the human body to eliminate liquid waste i.e. urea. It is often clear, odorless, and amber in color. The walls of bladder remain in ease while it reaches to fill its max and the urge to urinate grows greater. The brain sends signals to the bladder muscles, indicating it to tighten and squeeze the waste product out. It also indicates the sphincter muscles to relax, allowing urine to flow freely through the urethra [6,7].



**Figure 1. The Urinary system [6]**

Urinary Tract Infection mostly affects older adults and it is diagnosed in long term care residents frequently, therefore, accounting them to visits healthcare providers [8]. Researchers have created an algorithm that uses in-home sensory data to detect the risk of UTI. Early detection of a urinary tract infection is especially important for older persons, as delayed treatment can lead to more problems and be fatal. This Early detection of UTI symptoms not only allows for timely intervention and appropriate treatment, but it also allows for the identification of the source of other developing health issues such as confusion, agitation, or behavioral abnormalities. These symptoms are so common in patients with dementia, the underlying reason is frequently ignored which results in late UTI diagnosis and treatment.

Urinary Tract Infections are more common in women than in men, owing to their analysis; other risk factors for UTIs consider every situation that obstructs the flow of Urine [9,10]. UTIs are more likely in patients who have catheters or who have had urinary surgery, as well as those who have enlarged prostates. The symptoms and indicators of a urinary tract infection vary based on age, sex and the location of the urinary area infected; a few signs are specific to the afflicting agent. UTIs are normally detected by identifying the presence of urinary pathogen in the patient [11].

However, several home tests that can be used to provide a preliminary diagnosis of the infection. Although there are certain home cures for UTIs which at most assist to lessen

the risk or uneasiness of UTIs and cannot be thought as remedies for the illness. The complications of UTI include dehydration, sepsis and renal failure etc. Most individuals having UTI have a positive prognosis if these are treated promptly and effectively. Although there is no vaccine for UTIs but there are several strategies to lower the risk of having a complicated UTI [12].

### **1.1. Diagnosis of infection**

A urine sample is typically used to diagnose an infection. The white blood cells, red blood cells, and bacteria are analyzed in the sample. When dipped into urine, certain “test strips” coated with chemicals that responds by changing its color. These reagents react with a variety of substances found in urine, including yeast, bacteria, protein, and glucose. A microscope is used to examine the sample to check if there are any yeast or bacteria present and also its growth due to contamination. The bacteria found in the urine grow on a specific culture media. The type of bacteria present can be identified, and then antibiotics can be tested to see which ones are effective against the germs. The results or findings from cultures take at least two days to get ready; doctors will commonly treat the illness empirically with one of several medicines that are often effective. If the infection does not eliminate from the treatment, a urine culture is required to get tested and to check which antibiotic is most successful [13].

### **1.2. Symptoms of UTI**

**All are the symptoms of UTI in female contains:**

- Urge to urinate often in tiny amounts
- Burning when urinating
- Robust unpleasant urine odor
- Cloudy urine
- Crimson urine
- Fever, chills or back pain
- Other signs to look out for include bloating
- Vaginal discharge.
- Pelvic pain

**Symptoms of a urinary tract infection in males contains:**

- Wish to urinate on a regular basis, albeit in little amounts
- Urethral burning
- Strong unpleasant urine odour
- Rectal pain
- Cloudy urine
- Dark or bloody urine
- back or Flank discomfort (kidney infection) Penile, testicular and abdominal pain, as well as penile discharge, are all signs [14].

### 1.3. The risk for Urinary Tract Infection

All the factors that may raise the risk for UTI are as follows:

- **Insufficient voiding**

The bladder retains an excessive volume of urine and the bacteria are not entirely squeezed out with each time of urination.

- **Infrequent voiding**

The bacteria devote more time in the bladder, giving them more time to multiply and establish themselves.

- **Sexual Activity**

Trauma to the urethra and surrounding tissues can increase the infection vulnerability and bacteria can potentially be forcefully driven into the urethra.

- **Personal Hygiene**

Contamination of the Perineal with presence of faeces raises the chance of coliform bacteria in the vaginal canal and in the surroundings of urethra may raise the chances of UTI.

- **Usage of spermicidal contraception**

The spermicide itself alters the vaginal flora, causing more coliform bacteria to populate the area. The existence of certain types of bacterium increases the likelihood of a urinary tract infection.

- **Hormonal Status**

A deficiency of estrogen causes thinning and lack of tissue in the vaginal and urethral regions results in increasing the risk of UTIs. The deficiency of estrogen also alters the pH of the vagina, allowing more coliform bacteria to colonies and increasing the possibility of UTIs.

- **Genetics**

The vaginal mucosa and the urethra can both convey receptors that permit germs to adhere and drag themselves into the bladder, increasing the probability of a urinary tract infection [14].

### 1.4. Prevention

Some UTIs may be prevented by making lifestyle modifications. To prevent the risk of additional infections after menopause, a woman can apply estrogen cream to the vaginal area.

**Personal hygiene** Use sanitary pads as a substitute of tampons because some experts believe that tampons can increase the risk of infection. Each time go to the restroom, replace the sanitary pad.

- Do not use feminine hygiene sprays or powders or douche. In general, avoid using any perfume-containing products in the vaginal area.
- Instead of taking a bath, take a shower. Bath oils should be avoided.
- Maintain a clean genital region. Before and after sexual activity, clean genital and anal part.
- Urinate before and after have a sexual encounter.
- After using the restroom, wipe from front to back.

### **Clothing**

- Pants that are too tight should be avoided.
- Change Pantyhose and cotton clothes at least once a day.
- Always hydrated by drinking lots of water.
- Cranberry juice or cranberry tablets do not take.
- Avoid consuming irritants to the bladder, such as alcohol and caffeine [14].

### **1.5. Rates of recurrence of UTI**

In a 12-month follow-up study in Australia, there are 46 repeated UTI infections of 34/290 children; 20 children had one recurrence; 14 has two or more recurrences. A research from Sweden showed a recurrence of UTI in 32% of girls and 23% of girls under 10, although in girls two or more recurrences are far more likely (8 % versus 1 %). A minor research in the USA has also shown that girls are more likely to repeat themselves. A past research in Sweden showed a 26% recurrence in the neonates of both men; boys younger than 1 year old had an 18% recurrence rate, and boys over 1 year old has a 32% recurrence rate.

The recurrence rate for females older than 28 days was 40%. In one UK example, 41% of children less than 1 year of age has a history of UTI recurring to 73% over 5 years of age. The number with recurrent UTI rose with age in girls, but not in males. A prior investigation by the same Center revealed that the greater recurrences in children with renal parenchymal abnormalities despite the absence of elevated risks of recurrence for children with VUR. In another United Kingdom research, 78% of girls and 71% of boys who are previously of 1 year has additional infections, compared to 45% and 39% who has additional infection when people are after 1 year of age [15].

## **2. Major contributions**

Over the years, a surge in the number of people affected with UI has caused significant concern among healthcare experts all over the world. Furthermore, with adequate medical resources and incorporation of the upcoming IoT-Fog computing revolution along with enhanced data analysis methods are based on these aspects of the domain [17.18]:

- Use IoT technology-based sensors and preceptors to gather UI-related parameters. Based on infection degree, perform probabilistic classification of Urine Infection parameters into infection and non-infection categories (ID).

- At the fog computing layer, extract data using a temporal mining methodology to provide real-time service to users and make UI quantification in terms of infection index measure (IIM).
- Using the suggested temporal-artificial neural network (t-ANN) methodology, primary finding and forecast of Urinary Infection based on IIM value is possible.
- Information visualisation to the user in the manner of a colour coding technique for real decision-making in a timely manner. Table 1 shows the Embedded IoT Technology for Urine Analyzation.

**Table 1. IoT technology for analyzation of Urine**

S.No.	References	IoT Sensor	Utilized for
1	[19]	Raspberry Pi	Color, density, temperature
2	[20]	Optical Sensor	Urine creatinine
3	[21]	Fibre-grating Sensor	Protein
4	[22]	Electronic hydrometer	Particular gravity of urine
5	[23]	Intelligent catheter	PH, Temperature, pressure
5	[19]	Dipsticks	Urine nitrite
6	[24]	Bilirubin-optical sensor	Bilirubin
7	[25]	Urine active monitor system	Multiple UI

### 3. Literature review

This section of the paper reviews some major contributions in the area of Urinary Tract Infection monitoring, detection and prediction using recent technologies such as Internet of Things and Machine Learning. Also, some important related studies of diagnosis and predicting a disease are also considered based on current trends and technologies [16].

Gupta et al. (2022) proposed a fog computing-based framework using XGBoost algorithm that uses data collected from IoT based sensors and Infection risk factor for computation. The proposed model achieves the accuracy of 91.45% and considerably improved the performance level of the novel framework in comparison with the other baseline strategies [17].

Bhatia et al. (2020) proposed a smart framework for monitoring and predicting urine infection in home-based environment using internet of things. The proposed framework uses a model of 5 layers which consists perception layer, analysis layer, extraction layer,



prediction layer and visualization layer for determination of urine infection. The model is used for predicting the infection using t-ANN and achieves the accuracy of 93.69% [18].

Bhatia et al. (2020) presents a predictive system for urine based diabetes. The system consists of 4 layers such as data acquisition, data classification, mining and extraction and prediction and decision making for monitoring and predicting diabetes oriented infection. The proposed system uses recurrent neural networks for prediction and achieves the accuracy of 98.9%. WEKA tool is used for the implementation of the methods for comparative analysis [26].

Nyman & Jesper et al. (2020) said that the UTI is a frequent bacterial infection that involves both upper and lower urinary tract. Urine culturing can be utilized to diagnose the presence of infection. Culturing is time and money intensive, despite its precision. Flow cytometry analysis (FCA) technology is used for calculating numerous parameters, characteristics in a urine sample. The aim is to identify and understand different methods applied for screening and analyzing their performance before culturing. The prominent results were seen in random forest which minimizes the culturing load to 46 % and maintain both sensitivity and specificity at 95% and 72% respectively [27].

Kaur and Sharma (2019) presented a study to determine the occurrence of pathogens in urine sample and the susceptibility pattern of antimicrobial isolated from the samples from the suspected UTI affected infants. This study was conducted for two years on infants having the age greater than one year to check paediatric urinary tract infections. The results shows 15.7 % culture positivity rate, 70.1 % of male preponderance in UTI cases, bacterial isolation such as *Klebsiella* (16.7%), *E.coli* (45.4%) and *Enterococcus spp* (13.2%). Also, the isolates in the study are identified as resistant to atleast four antibiotics therefore this resistance to antibiotics becomes an important issue which needs to be addressed. [28].

Enshaeifar et al. (2019) discussed the use of technologies such as Internet of Things in combination with machine learning to keep track of person's health and well being. He developed an algorithm for UTI detection and tracking the changes in activity patterns in order to detect early signs of cognitive or health impairment and give individualized and preventative care. Also, an Isolation Forest (iForest) technique is employed to create a comprehensive perspective of everyday activity patterns. Suggested study outlines the algorithms and examines the work's evaluation using a large amount of real-world data from a trial with dementia patients and caregivers [29].

Uddin et al. (2019) represents a wearable sensor based system for detecting the activities related to healthcare sector. The proposed framework uses recurrent neural network for predicting the healthcare activities. The data inputs are taken from the various wearable sensors and then RNN is trained on the dataset. The proposed system provides the enhanced results as compared to the conventional techniques on the basis of experimental simulations [30].

Mohanty et al. (2019) suggested a smart water supply system for ICU patients. The suggested approach yielded encouraging results, although it was restricted to a hospital-

centric setting. Furthermore, in the suggested toilet system, the forecast of UI parameters was not accomplished.

Several data analytics techniques such as classification, clustering, and prediction are used in healthcare data modelling [31].

Zanetti et al. (2019) suggested a low-invasive IoT wearable device-based method for categorising mental stress levels. Several categorization algorithms are used to measure the mental stress level from the 3841 elements for this purpose. The mental state of volunteers are categorised as stressful cognitive, sustained attention and resting state. When compared with different classification algorithms, logistic regression and random forest classifiers had an improved accuracy of 84.6 % in the experimental application [32].

Catherwood et al. (2018) suggested a LoRa/Bluetooth-enabled electronic reader for biomedical strip-based diagnostics system for individualized observing, as well as a sophisticated IoT point-of-care bio-fluid analyzer. Also used a disposable test 'key' and companion Android app to form a diagnostic platform appropriate for remote point-of-care screening for UTI, and conduct test simulations (technology trials without patient subjects) to demonstrate the potential of long-range analysis, uses a disposable test 'key' and companion Android app to form a diagnostic platform appropriate for remote point-of-care screening for Urinary Tract Infection. The UTI test strips were visually reviewed for accurate diagnosis related to colour change and were found to be one hundred per-cent accurate [33].

Bae and Lee (2018) demonstrated a stationary UI monitoring solution. The authors proposes sensors based smart toilet used for analyzing urine components using Internet of Things. Cloud computing technology is used to store and analyse their findings. The suggested model, however, does not include performance estimators for time sensitivity and accuracy. Furthermore, results are only given to doctors in numerical cases [34].

Taylor et al. (2018) proposes a model for UTI prediction for the patients in emergency department. The objective is to have a comparison of all machine learning models after their training and validation with a large dataset of ED patients. The results show that XGBoost is the most prominent algorithm for diagnosing positive urine culture accurately. [35].

Falvey et al. (2018) showed a study that uses internet of things in order to improve the care of patients suffering from knee arthroplasty. To achieve this, Medicare's home-based health data of individuals with knee arthroplasty is used for analysis. The association between use of physiotherapy and patients' daily activities was determined using the multivariate linear regression data modelling approach. [36]

Gutte et al. (2018) presented an internet of things enables home-centric healthcare monitoring framework specifically for elderly patients. Raspberry Pi is used specifically for performing real time data computation. Also, LCD is used for result visualization for assessment of health data in real time. The outputs obtained from simulations depict certain improvements in comparison to the manual procedures for monitoring [37].



Amanda et al. (2017) introduce an analyzing breath sample of hypoglycaemic events in sort one polygenic disease patients: towards developing another polygenic disease alert dog. They used completely different tests for significance as well as Ranksum, Student's T-test, and distinction between means and located the presence of a set of fifty-six traces of metabolites. Also, a hypoglycemic signature appears to lie inside this cluster, according to principle element and linear discriminant analysis (LDA). Supervised machine learning combined with LDA reduced the list of seemingly elements to seven. The model shows 84% specificity and 91% sensitivity for hypoglycaemic identification [38].

Ke Yan and David Zhang (2016) projected model of a Breath Analysis System for diabetic blood sugar Level forecast and screening and design the UTI analysis system for diabetic detection aim. The system thoroughly chosen chemical from breath it observed by sensors to detect bio marker. Common factors like the programme considers humidity and the ratio of alveolar air in each breath. Construct subject-specific prediction models to increase the precision of Budget General Ledger (BGL) estimate by studying the inter-subject variance of the components in breath. Several categorization algorithms are used to measure the mental stress level from the 3841 features for this purpose. When compared to other classification algorithms, logistic regression and random forest classifiers has an improved accuracy of 84.6 % in the experimental application [39].

Sato et al. (2016) suggested the anesthesia which was maintained with oxygen–nitrous oxide inhalation till the delivery. 30 mg pentazocine and 5 mg diazepam are given immediately after delivery. However, the patient's blood pressure dropped sharply as a result of this. Moreover, during abdominal closure, seeping from the surgical field was noticed, and bleeding from the abdominal drain and oozing from the scar improved in the intensive care unit [40].

Moshaver et al. (2016) assess the benefits of using methods of flow cytometry for the positive urine culture prediction in order to decrease the number of urine cultures. He has taken 209 urine samples and out of which 79 were positive urine cultures. The specificity and sensitivity were 58 and 99% respectively. The method shows that FC can eliminate UTI [41].

Nickavar et al. (2015) performs a study on recognizing the predictive risk elements of urinary tract infection accompanied with hyperbilirubinemia in neonates. The aim is to identify the risks early and thereby reducing the long term complications. The results of the study shows that at the time of diagnosis UTI the mean age was  $16.37 \pm 8.86$  days and 70% of them was detected with hyperbilirubinemia. 37.5% patients show urinary tract abnormality in ultrasonography [42].

Eswari et al. (2015) describe the challenges of big data analytics in healthcare sector and the complications associated with Diabetic Mellitus disease. The developed system provides efficiency in curing and caring of affected people. He has included predictive testing for individuals with diabetes to decrease healthcare costs. Risk analysis for tailored health care was specifically conducted [43]. Chin and Tisan (2015) studied an IoT-based setup model for urine colour detection and integration for home-based

healthcare provisioning. The developed system uses myRio board and is based on the idea of RGB model. The analysis of presence of infection in the samples can be visualized on a Smartphone [44, 45]. This system provides benefits in achieving sustainable lifestyle.

Nayeem et al. (2015) have used ANN for diagnosis of disease. ANN is capable to learn nonlinear relationships and complex data. ANN is a broad category of elastic discriminating modelling techniques for non-linear dynamic systems like healthcare. Moreover, it is a useful modelling methodology for generalising new healthcare data pattern information, removing noise, and generating dependable and accurate outcomes. Furthermore, researchers have employed ANN to undertake non-linear statistical modelling to construct prediction systems for the medical business. Additional advantages of ANN in healthcare involve the ability to provide users with rapid and reliable operations and the creation of a simple measurable metric for complicated non-linear healthcare data [46].

Kharya (2012) suggested techniques of data mining for diagnosis of cancer disease. The authors uses Bayesian hybrid, ANN and C4.5 data modelling methodologies about health care framework for diagnosing breast cancer. The authors achieved maximum precision 86.7 % with c4.5, 86.5 with ANN and 84.5 with naïve bayes in the suggested model based on the various implementations [47].

Al-Shayea et al. (2010) stated that the data for suggested method obtained from the UCI Machine Learning Repository, and it was used to diagnose diseases. The information is divided into inputs and outputs. The symptoms will serve as the neural network's inputs. The neural network's targets will be identified as infected with 1s and non-infected with 0s. The feed-forward back propagation network properly classified 99 percent of the simulated sample in all situations. The findings suggest that the suggested diagnosis neural network could be useful in identifying infected individuals [48].

The purpose of the suggested method was to see how accurate urine sample collecting procedures were in children who were suspected of having UTI. Methods and Subjects. Dr. Sami Ulus Children's Hospital tested four strategies for collecting urine samples in 1,067 children aged 0–16 years with probable urinary tract infections over the course of two months. All specimens were sent to the laboratory within 30 minutes after collection, refrigerated, and processed according to routine hospital microbiological procedures [49].

An immunofluorescence test for the finding of antibody-coated bacteria in urinary sediments of patients UTI were examined to see if it could indicate where the infection was coming from. Antibody-coated bacteria were found in urine samples from 34 of 35 pyelonephritis patients, but not in urine samples from 19 of 20 cystitis patients. Most patients (20 of 28) who had antibody-coated bacteria in their urine had elevated serum antibody titers against the germs that had infected them. These findings imply that the immunofluorescence test may be beneficial in discriminating between kidney and bladder infections [50].

The improved effects are obtained in comparison to the state-of-the-art decision-making models based on the numerous simulations taken out by the inventors. Using a cloud-

based architecture, the system may assess and recommend drugs to patients. In comparison to existing methodologies, experimental outcomes for the suggested model are computed and better exactness is attained. Table 2 shows the summarize table of past related work.

High recurrence rates and increasing antimicrobial resistance among uropathogens threaten to greatly increase the economic burden of these infections. In this Review, we discuss how basic science studies are elucidating the molecular details of the crosstalk that occurs at the host–pathogen interface, as well as the consequences of these interactions for the pathophysiology of UTIs. We also describe current efforts to translate this knowledge into new clinical treatments for UTIs. High recurrence rates and increasing antimicrobial resistance among uropathogens threaten to greatly increase the economic burden of these infections. In this Review, we discuss how basic science studies are elucidating the molecular details of the crosstalk that occurs at the host–pathogen interface, as well as the consequences of these interactions for the pathophysiology of UTIs. We also describe current efforts to translate this knowledge into new clinical treatments for UTIs.

**Table 2. Summarize Table**

References	Aim	Outcomes
[17]	To early detect and predict the urine infection by using IoT sensors and Infection Risk Factor.	XGBoost algorithm with fog computing provide the accuracy of 91.45%
[18]	To detect and predict the infection in urine by identifying infection index measure.	t-ANN provide the accuracy of 93.69%.
[26]	Urine based diabetes prediction which uses internet of things to provide the better accuracy in detection of infection.	RNN provides the highest accuracy of 98.9%.
[27]	Suggested a Urine culturing which can be utilized to diagnose UTI.	The outcome is that the sensitivity was larger than 95%.
[28]	to evaluate the presence of pathogens in urine sample and the susceptibility pattern related to antimicrobial	the given framework has the capacity to generate alarms, communicate messages, and provide navigational route guidance.
[29]	developed an algorithm for detecting changes in activity patterns in order to detect early signs of cognitive or health impairment.	Examines the work's evaluation using a large amount of real-world data from a trial with dementia patients and caregivers.

[30]	To develop system based on wearable sensors for detecting health related activities.	RNN is used and provides efficiency as compared to other algorithms.
[31]	suggested a smart water supply system for ICU patients. The suggested approach yielded encouraging results.	Several data analytics techniques such as classification, clustering, and prediction are used in healthcare data modelling.
[32]	suggested a low-invasive IoT wearable device-based method for categorizing mental stress levels.	logistic regression and random forest classifiers had an improved accuracy of 84.6 % in the experimental application.
[33]	an advanced Internet of Things point-of-care bio-fluid analyzer; a LoRa/Bluetooth-enabled electronic reader for biomedical strip-based diagnostics system for personalised monitoring.	The UTI test strips were visually reviewed for correct diagnosis related to colour change and were found to be 100% accurate.
[34]	demonstrated a stationary UI monitoring solution.	Results are only given to doctors in numerical cases.
[35]	The objective to develop a predictive model and to have a comparison of all machine learning models after their training and validation with a large dataset of ED patients	XGBoost is the most prominent algorithm for predicting UTI with accuracy of 87.5%.
[36]	To provide improved healthcare to the patients suffering from knee arthroplasty.	Medicare home based data is used for analysis and logistic and negative regression is used for better performance.
[37]	Home-care-monitoring system using internet of things. It uses raspberry pi and LCD for implementation. This is specifically developed for old patient	It outperforms better than other conventional manual methods.
[38]	introduced Analyzing breath samples of hypoglycaemic actions in sort one polygenic disease patients towards developing another to polygenic disease alert dogs.	Proved a hypoglycemic signature seemingly resides inside this cluster. Supervised machine learning combined with LDA narrowed the list of seemingly elements to seven.
[39]	projected design of a Diabetic Screening and Blood Sugar Level	Several categorization algorithms are used to measure the mental stress level from the 3841 features for this purpose. When

	Prediction using a Breath Analysis System.	compared to other classification algorithms, logistic regression and random forest classifiers has an improved accuracy of 84.6 % in the experimental application.
[40]	suggested the anesthesia which was maintained with oxygen–nitrous oxide inhalation till the delivery.	surgical field was noticed and in the intensive care unit, bleeding from the abdominal drain and seeping from the scar intensified.
[41]	flow cytometry for the predicting positive urine culture prediction.	The method shows that FC can rule out UTI
[42]	recognizing the predictive risk elements of urinary tract infection	study shows that at the time of diagnosis UTI the mean age was $16.37 \pm 8.86$ days and 70% of them was detected with hyperbilirubinemia.
[43]	The aim is to use big data analytics in Diabetic Mellitus disease analysis and reducing the risk factors.	The developed system provides efficiency in curing and caring of affected people.
[44,45]	Internet of things based model for urine color detection and integration for home-based healthcare provisioning.	The RGB model is connected with smart phone and infection analysis can be seen on it. Its benefits in providing sustainable lifestyle.
[46]	ANN is employed to undertake non-linear statistical modelling to construct prediction systems	Model shows accuracy of 84% in case of heart diseases, 82% liver disorder and 91% in case of lung cancer.
[47]	suggested the Bayesian hybrid, ANN and C4.5 data modelling methodologies about health care framework for diagnosing breast cancer.	Achieved maximum precision 86.7 % in the suggested model based on the various implementations.
[48]	stated that the data for suggested study obtained from the UCI Machine Learning Repository, and it was used to diagnose diseases.	The findings suggest that the suggested diagnosis neural network could be useful in identifying infected individuals.

[49]	The purpose of suggested study was to see how accurate urine sample collecting procedures were in children who were suspected of having urinary tract infections.	All specimens were sent to the laboratory within 30 minutes after collection, refrigerated, and processed according to routine hospital microbiological procedures.
[50]	antibody-coated bacteria are detected in urine residues of patients with UTI.	Findings imply that the immunofluorescence test may be beneficial in discriminating between kidney and bladder infections.

Table 3 shows the Comparative Analysis on UTI prediction in which numerous applications are utilized for tracking the Urine Infection.



**Table 3. Comparative Analysis of Related Studies**

<b>Metrics</b>	Bhatia, Munish, et al. [14]	Gutte and vadali (2018) [33]	Taylor et al. (2018) [31]	Mohanty (2019) [27]	Falvey et al. (2018) [32]	Chin and Tisan (2015) [40]	Uddin (2019) [26]	Bae and Lee (2018) [30]	Catherwood et al. (2018) [27]	Bhatia, Munish, et al. [22]
<b>Utilization Domain</b>	Home-centric UTI Prediction	Smart Home-Health Tracking	Urinary Tract Infection prediction in emergency department.	IoT-based Toilet System for ICU patients	Home centered healthcare	Smart Pervasive Hydration Tracker	Activity Prediction Healthcare System	Urinary Infection Monitoring	Home Based Health Monitoring	Ubd prediction System for Health care
<b>Insights</b>	Framework based on IoT for monitoring of urine infection and its prediction.	Development of Smart Health Monitoring System	Development and analysis of predictive models for UTI detection and prediction.	Designing Fuzzy logic based PID controller	Healthcare utilization for patient in Home-care settings detection	Development of Body Hydration System using dual-core ARM processor	Wearable IoT based system activity prediction	Smart Toilet System	Innovative IoT Bio-analyzer	Ubd Monitoring and prediction System
<b>Mathematical Modeling</b>	Available	-	-	-	-	-	-	-	-	Available
<b>Predictive Analytics</b>	Probabilistic prediction	-	Available	-	-	-	Available	-	-	(Probabilistic Prediction)
<b>Data Collection Techniques</b>	IoT Sensors	Sensors	HER	Wired Sensors	-	IoT Sensors	Sensors	IoT sensors	IoT Sensors	Smart IoT Sensors, and

										Preceptors
<b>Data Modeling Repository</b>	Cloud and local	Cloud	Local	-	Local	Cloud	Local	Cloud	Cloud	Cloud and File.
<b>Implementation Results</b>	Color coded mechanism	Text	Text	-	Text	Graphical	Text	Text	Text	Color Coded mechanism
<b>Response Formats</b>	Color graphics and textual	Homogeneous	Textual	-	Textual	Heterogeneous	-	Textual	Textual	Textual, Color graphics
<b>Dataset</b>	Heterogeneous and Homogeneous	-	Heterogeneous and Homogeneous	-	-	-	-	Heterogeneous	-	Heterogeneous and Homogeneous
<b>Data Security</b>	SSL	-	-	Available	-	Available	Available	-		SSL

## Comparative Discussion

This section of the paper presents a comparative discussion between the related studies of detecting and predicting Urinary Tract Infection. As per the literature review there are various studies that show the different methodologies for detecting and predicting the infection and diseases in the healthcare sector. Specifically, for comparison Bae and Lee [34], Taylor [35], Mohantay and Mohantay[31], Munish Bhatia et al.[18], Munish Bhatia et al.[26] challenging studies are observed.

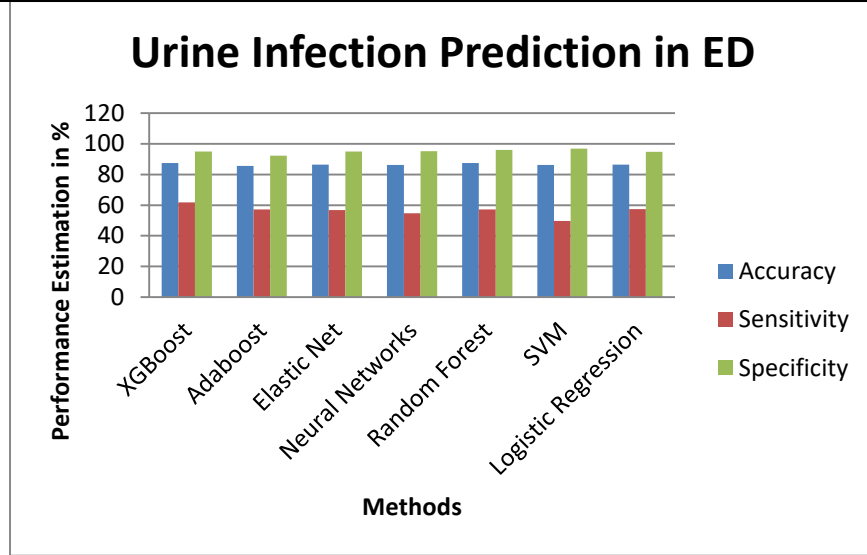
Bae and Lee[34] discussed the use of recent technology integration in healthcare sector. They utilize Internet of Things for diagnostic and analysis of urine components and developed a smart toilet for UI monitoring. The urine components taken for analysis are leukocysts, Nitrite, Urobilinogen, Bilirubin, PH value, Blood, Protien, Ketones, Glucose and Specific Gravity. The cloud computing is used as a data repository for the system. However, the limitation is that the system does not provide results in visual representation as it is a static identification system for urine analysis. Also, as there is no predictive model is used with the system, therefore, performance estimators such as accuracy, sensitivity and specificity are not included. Mohantay et al.[31] analyzed a case study regarding water supply for a semiautomatic toilet system of ICU patients. The system discussed in the paper contains no analysis of urine culture and restricted its application specifically to a home-centric environment. However, the overall scheme presents promising results as output in simulations.

There are studies which consider performance estimators and use various algorithms for comparison. Likewise, algorithms are: Stochastic gradient descent (SGDR), Support Vector Machine (SVR), ANN, t-ANN, Defect-Tolerant Routing (DTR), k-NNR, GBDT, ADABOOST, adaptive network-based fuzzy inference system (ANFIS), Random Forest Regression (RFR), and Recurrent Neural Network (RNN). Taylor et al.[35] uses machine learning for predicting UTI in emergency department. The dataset taken in the study is having 80,387 data instances. The model is developed with seven machine learning algorithms for UTI prediction. The development of the model is done with 211 variables as full dataset and 10 variables (UI parameters) as reduced dataset. The study evaluates the models on the basis of accuracy, sensitivity and specificity and the results of data set are shown in the table 3.

**Table 4. Performance Results in percentage**

Methods	Accuracy	Sensitivity	Specificity
XGBoost	87.5	61.7	94.9
Adaboost	85.6	57.3	92.3
Elastic Net	86.4	56.8	94.9

Neural Networks	86.3	54.6	95.3
Random Forest	87.4	57.3	96.0
SVM	86.3	49.6	96.8
Logistic Regression	86.4	57.5	94.7



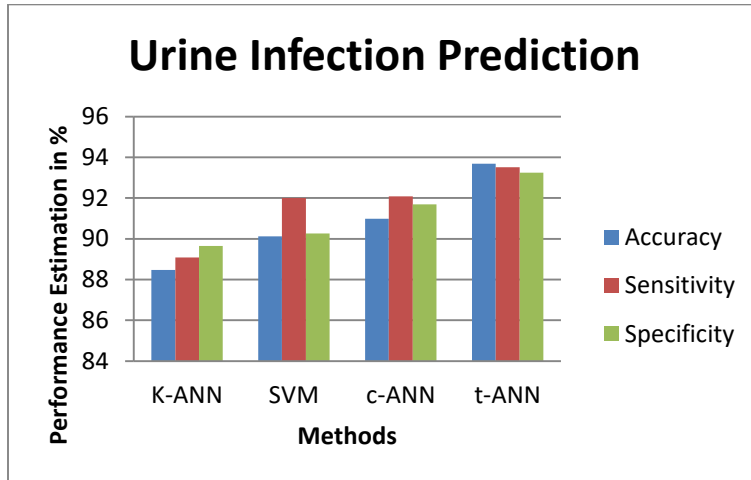
**Figure 2: Urine Infection Prediction in ED**

This shows that for the detailed dataset of 211 variables XGBoost is the most prominent one among all the others methods but for the reduced dataset of 10 variables, XGBoost and neural network are same in accuracy but. In this study, the data is taken form a healthcare institution and is limited to each emergency department visit.

Bhatia et al. [18] proposes a home-centric framework for UI prediction using internet of things. It provides real-time monitoring and analysis of UI parameters with respect to infection index measure. The study consists of tracking 12 patients for 14 days continuously and collects approximately 3528 datasets. The t-Ann is used in the proposed model for prediction of UI and the performance is evaluated. The results of the study are as shown below in the table 4.

**Table 5. Performance Results in percentage**

Methods	Accuracy	Sensitivity	Specificity
K-ANN	88.47	89.08	89.65
SVM	90.12	92.01	90.27
c-ANN	90.99	92.09	91.69
t-ANN	93.69	93.51	93.25



**Figure 3: Urine Infection Prediction**

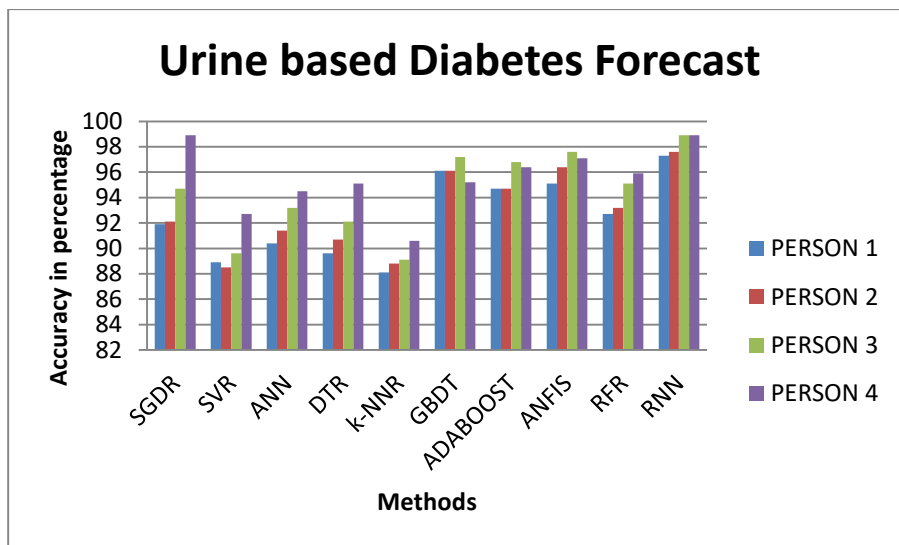
This shows that t-ANN has the highest accuracy among K-ANN, SVM and c-ANN. It can be said that the system developed is effective and efficient in detecting and predicting Urinary Infection.

In another study of Bhatia et al.[26] presented a study on urine based effective detection and prediction of diabetes. Urine parameters used in the study are color, saltiness, PH value, bilirubin, specific gravity and density. The dataset comprise of 8569 data instances acquired from four persons. Data instances of person1, person2, person3, person4 are 2123, 2103, 2155 and 2188 respectively. The developed system uses heterogeneous physiological parameters and for the baseline classifiers it uses Decision Tree and SVM. Also, the system uses SOM for better visualization effectiveness.

Several methods are compared on the four person's dataset to find the accuracy of the developed model which uses RNN. The accuracy of all the four persons are as shown in the Table 5.

**Table 6. Accuracy Results in percentage**

METHODS	PERSON 1	PERSON 2	PERSON 3	PERSON 4
SGDR	91.9	92.1	94.7	98.9
SVR	88.9	88.5	89.6	92.7
ANN	90.4	91.4	93.2	94.5
DTR	89.6	90.7	92.1	95.1
k-NNR	88.1	88.8	89.1	90.6
GBDT	96.1	96.1	97.2	95.2
ADABOOST	94.7	94.7	96.8	96.4
ANFIS	95.1	96.4	97.6	97.1
RFR	92.7	93.2	95.1	95.9
RNN	97.3	97.6	98.9	98.9



**Figure 4: Urine Based Diabetes Forecast**

The results show that in the provided UbD forecast arrangement, the suggested system outperformed alternative group and baseline and systems with small differences in the Person 1 dataset by 97.3 %. For the Person 2 dataset, the recommended system produced a 97.6 % value that was higher than other systems. Moreover, the suggested method can achieve 98.9 % accuracy for the Person 3 and Person 4 datasets, respectively.

According to these results, the recurrent neural network for prediction can be assumed to be exceptionally accurate in the current circumstance. Also, the results obtained in the study is compared to all other related studies and it can be concluded that the system developed is capable to outperform all the other methods in terms of efficiency, temporal delay, prediction efficiency classification and stability analysis[26].

## Conclusion

- The Bacteria that enter the urinary tract result in occurrence of an inflammation and infection. The untreated UTI increases the risks of several diseases associated with liver, kidneys and bladder.
- Several methodologies are considered for early detection and prediction of UTI and as per the comparative analysis among different studies in literature review, RNN gives effective forecast analysis related to the temporal features of UbD characteristics, which have been defined in terms of Diabetic Infection Measure (DIM) and Level of Diabetic Infection (LoDI). The system on a module (**SOM**) based methodology has been used to improve the suggested system's visualization effectiveness.
- As a result, it is determined that the UI prediction model is both dependable and accurate. Incorporating energy competence for home-based monitoring is an



essential subject to investigate in future study. Another component of reducing hospitalizations and healthcare resource use is linked remote doctor intrusion and home-centric healthcare for smart homes.

## Declaration

**Author Contributions:** Anisha wrote and organized the manuscript. Dr. Munish Sabharwal and Dr. Rohit Tripathi read and corrected the manuscript.

**Conflict of interest:** The authors declare that there is no conflict of interest regarding the publication of this paper.

## References

- [1]. Buyya, R., Yeo, C. S., Venugopal, S., Broberg, J., & Brandic, I. (2009). Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility. *Future Generation computer systems*, 25(6), 599-616.
- [2]. Bhatia, M., & Sood, S. K. (2016). Temporal informative analysis in smart-ICU monitoring: M-HealthCare perspective. *Journal of medical systems*, 40(8), 1-15.
- [3]. Manogaran, G., Varatharajan, R., Lopez, D., Kumar, P. M., Sundarasekar, R., & Thota, C. (2018). A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system. *Future Generation Computer Systems*, 82, 375-387.
- [4]. Flores-Mireles, A. L., Walker, J. N., Caparon, M., & Hultgren, S. J. (2015). Urinary tract infections: epidemiology, mechanisms of infection and treatment options. *Nature reviews microbiology*, 13(5), 269-284.
- [5]. Shahid, N., Rappon, T., & Berta, W. (2019). Applications of artificial neural networks in health care organizational decision-making: A scoping review. *PloS one*, 14(2), e0212356.
- [6]. Walentowicz, M., Krzemiński, D., Kopański, Z., Liniarski, M., Tabak, J., Dyl, S., ... & Mazurek, M. (2017). Selected aspects of the urinary system anatomy and physiology. *Journal of Clinical Healthcare*, 89(2017\_3), 01-05.
- [7]. Bono, M. J., & Reygaert, W. C. (2021). Urinary tract infection. *StatPearls* [Internet].
- [8]. Rowe, T. A., & Juthani-Mehta, M. (2014). Diagnosis and management of urinary tract infection in older adults. *Infectious Disease Clinics*, 28(1), 75-89.
- [9]. Ameen, W. A., & Hummade, S. H. (2015). Risk factors for urinary tract infection among women at productive age at Babel Technical Institute in Hilla city. *Age*, 16(20), 44.
- [10]. Czajkowski, K., Broś-Konopielko, M., & Teliga-Czajkowska, J. (2021). Urinary tract infection in women. *Przegląd Menopauzalny= Menopause Review*, 20(1), 40.
- [11]. Najjar, M. S., Saldanha, C. L., & Banday, K. A. (2009). Approach to urinary tract infections. *Indian journal of nephrology*, 19(4), 129.
- [12]. Schmiemann, G., Kniehl, E., Gebhardt, K., Matejczyk, M. M., & Hummers-Pradier, E. (2010). The diagnosis of urinary tract infection: a systematic review. *Deutsches Ärzteblatt International*, 107(21), 361.
- [13]. Chu, C. M., & Lowder, J. L. (2018). Diagnosis and treatment of urinary tract infections across age groups. *American journal of obstetrics and gynecology*, 219(1), 40-51.
- [14]. Komala, M., & Kumar, K. S. (2013). Urinary tract infection: causes, symptoms, diagnosis and its management. *Indian Journal of Research in Pharmacy and Biotechnology*, 1(2), 226.
- [15]. National Institute for Clinical Excellence. (2003). National collaborating centre for women's and children's health. Caesarean section: clinical guideline.

- [16]. Kumar, Y., Gupta, S., & Gupta, A. (2021, November). Study of Machine and Deep Learning Classifications for IOT Enabled Healthcare Devices. In 2021 International Conference on Technological Advancements and Innovations (ICTAI) (pp. 212-217). IEEE.
- [17]. Gupta, A., & Singh, A. (2022). Early Urine Infection Prediction Framework using XGBoost Ensemble Model in IoT-Fog Environment.
- [18]. Bhatia, M., Kaur, S., & Sood, S. K. (2020). IoT-inspired smart home based urine infection prediction. *Journal of Ambient Intelligence and Humanized Computing*, 1-15.
- [19]. Richards, D., Toop, L., Chambers, S., & Fletcher, L. (2005). Response to antibiotics of women with symptoms of urinary tract infection but negative dipstick urine test results: double blind randomised controlled trial. *Bmj*, 331(7509), 143.
- [20]. Erenas, M. M., Carrillo-Aguilera, B., Cantrell, K., Gonzalez-Chocano, S., de Vargas-Sansalvador, I. M. P., de Orbe-Payá, I., & Capitan-Vallvey, L. F. (2019). Real time monitoring of glucose in whole blood by smartphone. *Biosensors and Bioelectronics*, 136, 47-52.
- [21]. Guo, J. Y., & White, E. (2016, January). Autophagy, metabolism, and cancer. In *Cold Spring Harbor symposia on quantitative biology* (Vol. 81, pp. 73-78). Cold Spring Harbor Laboratory Press.
- [22]. Guay, R., & Moffatt, P. R. (1983). U.S. Patent No. 4,400,978. Washington, DC: U.S. Patent and Trademark Office.
- [23]. Kalb, I. M., Shaw, R. H., & Ram, M. J. (1998). U.S. Patent No. 5,704,353. Washington, DC: U.S. Patent and Trademark Office.
- [24]. Çiçek, Ç., Yılmaz, F., Özgür, E., Yavuz, H., & Denizli, A. (2016). Molecularly imprinted quartz crystal microbalance sensor (QCM) for bilirubin detection. *Chemosensors*, 4(4), 21.
- [25]. Seo, W., Yu, W., Tan, T., Ziaie, B., & Jung, B. (2017). Diaper-embedded urinary tract infection monitoring sensor module powered by urine-activated batteries. *IEEE transactions on biomedical circuits and systems*, 11(3), 681-691.
- [26]. Bhatia, M., Kaur, S., Sood, S. K., & Behal, V. (2020). Internet of things-inspired healthcare system for urine-based diabetes prediction. *Artificial Intelligence in Medicine*, 107, 101913.
- [27]. Nyman, J. (2020). Machine learning approaches for detection of urinary tract infections.
- [28]. Kaur, N., Sharma, S., Malhotra, S., Madan, P., & Hans, C. (2014). Urinary tract infection: aetiology and antimicrobial resistance pattern in infants from a tertiary care hospital in northern India. *Journal of clinical and diagnostic research: JCDR*, 8(10), DC01.
- [29]. Enshaeifar, S., Zoha, A., Skillman, S., Markides, A., Acton, S. T., Elsaleh, T., ... & Barnaghi, P. (2019). Machine learning methods for detecting urinary tract infection and analysing daily living activities in people with dementia. *PloS one*, 14(1), e0209909.
- [30]. Uddin, M. Z. (2019). A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system. *Journal of Parallel and Distributed Computing*, 123, 46-53.
- [31]. Mohanty, M. D., Pattnaik, D., Parida, M., Mohanty, S., & Mohanty, M. N. (2019). Design of intelligent pid controller for smart toilet of ccu/icu patients in healthcare systems. In *International conference on intelligent computing and applications* (pp. 97-107). Springer, Singapore.
- [32]. Zanetti, M., Mizumoto, T., Faes, L., Fornaser, A., De Cecco, M., Maule, L., ... & Nollo, G. (2021). Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices. *Journal of Ambient Intelligence and Humanized Computing*, 12(4), 4409-4418.
- [33]. Catherwood, P. A., Steele, D., Little, M., Mccomb, S., & McLaughlin, J. (2018). A community-based IoT personalized wireless healthcare solution trial. *IEEE journal of translational engineering in health and medicine*, 6, 1-13.
- [34]. Bae, J. H., & Lee, H. K. (2018). User health information analysis with a urine and feces separable smart toilet system. *Ieee Access*, 6, 78751-78765.
- [35]. Taylor, R. A., Moore, C. L., Cheung, K. H., & Brandt, C. (2018). Predicting urinary tract infections in the emergency department with machine learning. *PloS one*, 13(3), e0194085.

- [36]. Falvey, J. R., Bade, M. J., Forster, J. E., Burke, R. E., Jennings, J. M., Nuccio, E., & Stevens-Lapsley, J. E. (2018). Home-health-care physical therapy improves early functional recovery of Medicare beneficiaries after total knee arthroplasty. *The Journal of bone and joint surgery. American volume*, 100(20), 1728.
- [37]. Gutte, R Vadali, IoT Based Health Monitoring System Using Raspberry Pi, 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, 1-5, DOI:10.1109/ICCUBEA.2018.8697681
- [38]. Siegel, A. P., Daneshkhah, A., Hardin, D. S., Shrestha, S., Varahramyan, K., & Agarwal, M. (2017). Analyzing breath samples of hypoglycemic events in type 1 diabetes patients: towards developing an alternative to diabetes alert dogs. *Journal of Breath Research*, 11(2), 026007.
- [39]. Yan, K., & Zhang, D. (2016). Calibration transfer and drift compensation of e-noses via coupled task learning. *Sensors and Actuators B: Chemical*, 225, 288-297.
- [40]. Sato, Y., Hamaguchi, S., Numata, Y., Komatsuzaki, M., & Yamashita, Y. (2016). Anesthetic Management of A Patient who Underwent Emergent Cesarean Section after Sudden Disturbance of Consciousness Caused by Disseminated Intravascular Coagulation due to Severe Urine Infection and Septic Shock. *J Anesth Clin Res*, 7(613), 2.
- [41]. Moshaver, B., de Boer, F., van Egmond-Kreileman, H., Kramer, E., Stegeman, C., & Groeneveld, P. (2016). Fast and accurate prediction of positive and negative urine cultures by flow cytometry. *BMC infectious diseases*, 16(1), 1-7.
- [42]. Nickavar, A., Khosravi, N., & Doaei, M. (2015). Early prediction of urinary tract infection in neonates with hyperbilirubinemia. *Journal of renal injury prevention*, 4(3), 92.
- [43]. Eswari, T., Sampath, P., & Lavanya, S. J. P. C. S. (2015). Predictive methodology for diabetic data analysis in big data. *Procedia Computer Science*, 50, 203-208.
- [44]. Chin, J., & Tisan, A. (2015, July). An IoT-based pervasive body hydration tracker (PHT). In 2015 IEEE 13th International Conference on Industrial Informatics (INDIN) (pp. 437-441). IEEE.
- [45]. Dastjerdi, A. V., & Buyya, R. (2016). Fog computing: Helping the Internet of Things realize its potential. *Computer*, 49(8), 112-116.
- [46]. Nayeem, M. O. G., Wan, M. N., & Hasan, M. K. (2015). Prediction of disease level using multilayer perceptron of artificial neural network for patient monitoring. In *International Journal of Soft Computing and Engineering (IJSCE)* (Vol. 5, No. 4, pp. 17-23).
- [47]. Kharya, S. (2012). Using data mining techniques for diagnosis and prognosis of cancer disease. arXiv preprint arXiv:1205.1923.
- [48]. Al-Shayea, Q. K., & Bahia, I. S. (2010). Urinary system diseases diagnosis using artificial neural networks. *International Journal of Computer Science and Network Security (IJCSNS)*, 10(7), 118-122.
- [49]. Karacan, C., Erkek, N., Senel, S., Gunduz, S. A., Catli, G., & Tavil, B. (2010). Evaluation of urine collection methods for the diagnosis of urinary tract infection in children. *Medical Principles and Practice*, 19(3), 188-191.
- [50]. Pimenta, J. M., Catchpole, M., Rogers, P. A., Perkins, E., Jackson, N., Carlisle, C. & Ghosh, A. (2003). Opportunistic screening for genital chlamydial infection. I: Acceptability of urine testing in primary and secondary healthcare settings. *Sexually transmitted infections*, 79(1), 16-21.