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An Automated Healthcare Monitoring Architecture Employing Wearable Sensors and Social-Media Data

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Abstract: Wearable sensor (WS) technology and social media platforms (SMPs) are increasingly being used to monitor healthcare, and this has opened up new possibilities as chronic illnesses become more common. The development of a novel technique for gathering patient data for effective healthcare monitoring relies heavily on WS and SMP. But WS-based continuous patient monitoring produces a great deal of healthcare data. Furthermore, the user-generated health information on social networking sites is unstructured and produced in massive amounts. The current healthcare monitoring systems struggle to adequately analyze the useful information that may be gleaned from social networking and sensor data. Additionally, processing healthcare big data for anomaly prediction does not work well with conventional machine learning methods. Therefore, the purpose of this study is to propose an automated healthcare monitoring system for better categorization accuracy via accurate data storage and analysis. A novel fuzzy binary temporal long short-term memory (FBTLSTM) approach is used to appropriately categorize healthcare data and forecast drug side effects and abnormal conditions in patients. Patients' healthcare data, including diabetes, blood pressure, mental health, and drug evaluations, is used to categorize their health status in the proposed system. The findings demonstrate that the suggested model accurately manages heterogeneous data, enhances the categorization of medical conditions, and improves the predictability of drug side effects.

Keywords*: Healthcare monitoring (HM), wearable sensors (WS), social media data (SMD), fuzzy binary temporal long short-term memory (FBTLSTM)*

1. Introduction

The process of regularly observing and evaluating an individual's health to detect any anomalies, changes, or possible concerns is known as healthcare monitoring. An automated healthcare monitoring architecture is a framework or system that uses technology to continuously and automatically monitor and manage people's health and well-being. The integration of numerous components, including sensors, data-gathering techniques, data-processing algorithms, and communication systems, is common for this design [1]. Small electronic devices are known as WS are created to be carried on the body or incorporated into apparel or accessories. They have a range of sensors that can gather information on a person's activities, habits, and physiological factors. These sensors make it possible to continuously monitor health-related data and provide useful information on a person's health [2]. Information created and shared by users on different social media frameworks is referred to as SMD. It comprises interactions, activities, user-generated content, and demographic data. Users may establish and publish updates, profiles, connect with others, share images and videos, and participate in discussions on social networking sites like Facebook, Twitter, Instagram, LinkedIn, and YouTube. Integration of SMD with a healthcare monitoring framework enables a greater comprehensive recognition of an individual's health and behavior [3]. Social media is an effective source of information that has grown to be important for researching many facets of ordinary life. Social media's distinguishing characteristics, such as interaction, the capacity to build communities on the internet, real-time data, geolocation capabilities, and demographic penetration, point to a potential use for this technology in disease surveillance and health promotion. Patients, medical professionals, and researchers may all benefit from better information thanks to social media. More importantly, they encourage the sharing of medical expertise and knowledge. Social media may help healthcare organizations interact with patients and improve the patient experience. Additionally, by bridging the gap between researchers and doctors, scientific advancements are made more accessible to doctors. In an ever-evolving sector, information learned through this tighter interaction

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with researchers may direct clinicians' choices about patient treatments [4]. WS is built using a variety of WS for monitoring the patient. An HMS's fundamental component is a sensor, which is often wearable. Through a statement technology like Wi-Fi or Bluetooth, ZigBee, information collected by the sensor is relayed to the internet. These data are then transmitted to the data center for additional processing through a communication layer. The doctor, patient, and the patient's caregivers may all view the same information in real-time to spot any emergencies [5]. Wearable technologies powered by environmental sensing can continually track human physiology and difficulties. The prompt diagnosis and treatment of life-threatening occurrences such as arrhythmias, myocardial infarction, and strokes. High-risk collections, those with above usual body mass indices, may be encouraged to become active and modify their lifestyles by comparable monitoring and ongoing tracking of their well-being and health [6]. Since the introduction of smartphones and other movable devices, WS developed a lot of consideration outstanding to their beneficial insights regarding the performance and health of individuals. The initial study in the field concentrated on physical sensors that tracked movement as well as important indicators including heart rate, steps, and watts burnt. They have moved away from pursuing physical movement to concentrate on addressing significant difficulties in healthcare programs, such as the treatment of diabetes or remote monitoring of the elderly, changing the face of wearable technology quickly in recent years [7]. The usage of wearable and sensing devices is not without its difficulties. First off, their usage as health applications may be constrained by the fact that they are frequently thought of as consumer commodities. Second, they can alter how health care is delivered and influence how sensitive personal data is gathered and shared. For instance, unlike the sporadic nature of clinical consultations, continuous monitoring data gathered through IoT technology has the potential to enhance the information base for decision-making. Patients might not want to be tracked, and healthcare professionals already feel overloaded with data. Furthermore, research in the area of trustworthy computing has demonstrated that systems frequently generate false-positive warnings, casting doubt on the effectiveness of these applications. Unintended repercussions from such problems may result in subpar patient outcomes and safety hazards. Particular privacy and confidentiality considerations apply to healthcare data, and there are additional protections in place. Therefore, there are new complexities around information privacy, data sharing, autonomy, permission, ownership, data access, and data valuation when wearable sensor devices are used in the healthcare industry [8]. In this paper, we proposed (LBTLSTM) techniques for categorizing healthcare information.

2. Related Work

The study [9] established to first determine whether it was feasible to treat hospitalized patients with sepsis using WS rather than conventional bedside monitors, and second, to propose autonomous models of prediction for sepsis patient fatality prediction. In LMICs, managing critical care for sepsis is difficult since there aren't enough healthcare professionals and bedside monitors are expensive. The research [10] analyzed and assessed different methods for stress detection that utilize low-cost WS to gather information and machine learning algorithms to forecast an individual's degree of stress. Stress is a sense of being put under excessive strain that stems from several facets of daily living. Stress management is crucial to maintain a low-stress level and lower health risks because stress is one of the main contributors to serious chronic health issues. The paper [11] performed a systematic analysis of the most recent digital developments in Healthcare 4.0 using the wisdom pyramid technique. A phrase that just came into use and was taken from the term Industry 4.0 is Healthcare 4.0. Healthcare manufacturing is more digital consequently than it was in the previous decade, for x-rays, for instance, magnetic resonance imaging, ultrasound scans, computed tomography, and electronic medical records are all forms of digital imaging. The study [12] presented a novel multi-sensor system for monitoring lung function, including breathing rate and tidal volume. They describe a fresh effort to create a compact, all-inclusive wearable sensor system to track respiration utilizing a multi-sensor strategy. To monitor different health parameters on two volunteers, they used innovative WS equipment that involved a unique integration of acoustics and biopotentials. The article [13] provided an overview of all the key ideas, including IoT, AI, and 5G connectivity, to model Healthcare 5.0. The introduction of the artificial intelligence (AI) idea, together with the use of smart, intelligent gadgets and the use of high-speed information transfer methods in the healthcare sector, elevated the bar for healthcare philosophy to a new level. The research [14] suggested an end-to-end remote surveillance system for computerized diabetes risk prediction and management employing smartphones, wearables, and personal health equipment. Annually, millions of people are affected by the metabolic disorder known as diabetes. It has been linked to a lower standard of living and a greater risk of fatal organ failure. Diabetes must be managed with early identification and ongoing monitoring. With the use of modern technology, remote patient monitoring can promote efficient treatment and intervention approaches. The paper [15] described the critical function of IoT and cloud activity monitoring systems for senior healthcare in medicine to lessen the demand for caregivers and support older people in maintaining an active lifestyle. Additionally offers a framework for a wearable body sensor network-based intelligent IoT and cloud activity monitoring system for the care of old people. The paper [16] examined the patient's health remotely using wearable IoT sensors, the cloud, and web layers. The Internet of Things was used in the study to monitor COVID-19 patients. IoT-based real-time GPS data collection assists in immediately alerting the patient to lower risk factors. To study data for making judgments about health conditions, wearable IoT devices are affixed to people's bodies and connected with edge nodes. The study [17] suggested ascertaining if two wearable patch sensors, a bed-based system called Health Patch, and a patient-worn monitor could accurately track patients' heart rates and respiration rates while they were recovering from major surgery. Researchers have created wireless sensors that might detect patient decline early. Patients at the hospital ward often have their vital signs taken once every eight hours. Thus, early indications of decline can be overlooked. The article [18] developed an accurate automated method for tracking patient health so that doctors or other healthcare professionals may assess and keep tabs on patients who are either in hospitals or going about their regular daily business. The greatest issue facing humanity on a global scale is health. The last 10 years have seen a considerable increase in media coverage of the healthcare industry. The research [19] examined the functions and capabilities of sensors, as well as those of other cutting-edge technologies, including blockchain, robots, big data, the Internet of Things, artificial intelligence, and cloud computing. It is necessary to integrate intelligent sensors and health systems through developing technologies since there is a lack of emotional recognition, as well as a lack of tailored and ubiquitous health apps and emotive smart devices. The study [20] suggested a novel sensor-based human activity recognition (HAR) with an outstanding ability to categorize complicated activities using a deep learning model called the InceptTime network. In big data applications like ambient healthcare-supported living, accurate HAR might be quite helpful. The study of HAR has greatly progressed thanks to DL techniques. In terms of automated extraction of features, these deep learning algorithms beat traditional machine learning techniques. Numerous deep learning models have recently been shown to be cutting-edge methods for effectively classifying both basic and complicated human activities to solve the HAR.

3. Proposed Methodology

A healthcare monitoring architecture employing WS and SMD can provide valuable insights into an individual's health and well-being. Data from this study is to propose an automated healthcare monitoring system for better categorization analysis, then pre-processed using the Min-max Normalization and feature extraction for Linear Discriminant Analysis (LDA). We propose an innovative FBTLSTM technique for categorization. The suggested block diagram is shown in Figure 1.

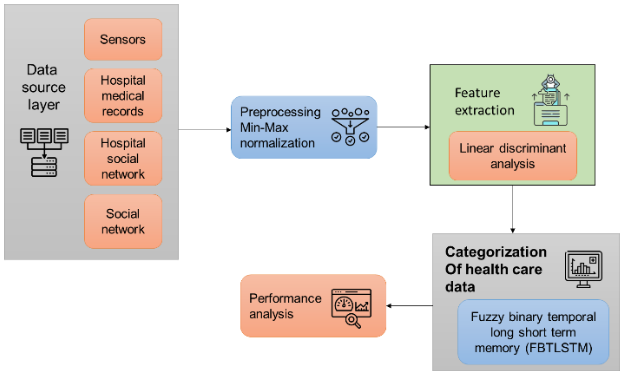

Fig.1. Block diagram of proposed

3.1. Data collection

The data for this suggested system is gathered from four separate sources. We discuss in great detail about each of the four data gathering methods in this section [21].

3.1.1 Wearable devices

Glucometer sensors, Blood pressure monitors, pulse oximeters, smart watches, temperature sensors, accelerometers, and weigh scales are just some examples of smart sensors and WS that can be used to track a patient's vitals in real-time. In our strategy, patients are outfitted with WS that monitors their health indicators in real-time. The popularity of smartphones is at an all-time high, and health-related applications have come a long way in recent years. The sensors included in a smartphone provide accurate information collected from a wide range of anatomical locations. Therefore, people with diabetes and high blood pressure use their smartphones to record their diet, exercise routines, and various activities, in addition to their private details. This data is useful for both patient disease and care prevention. The data stored on a smartphone, however, is particularly vulnerable to loss. The difficulty of sifting through smartphone data to get useful health insights. To organize sensing information and extract useful information for effective use, they have employed ontology-based semantic knowledge and data mining methodologies.

3.1.2 Medical records

Medical records provide information on the therapies that individuals with diabetes and high blood pressure received. Patient's medical records, which include their medical records. By analyzing these files, doctors may be able to better establish criteria for diagnosing diabetes and hypertension. However, medical files can be lengthy and complicated due to the large amounts of information they include. Additional complications, including renal and cardiovascular illness, neuropathy, skin and eye problems, and neuropathy, may affect patients with diabetes and high blood pressure. Therefore, it is essential to review patient medical records to identify people who are experiencing the aforementioned challenges and to monitor their improvement via more in-depth evaluations.

3.1.3 Data from social networking platforms and webpages

This involves more work and is sensitive to the security settings of each social media platform. It's important to note that not all social media platforms provide their APIs for developers to use. In such a scenario, information extraction applications like wrappers may be used. Patients with chronic conditions like diabetes and hypertension need to have regular doctor's appointments, however, they also need the resources, information, and abilities to manage their health. Patients aren't getting useful data from their healthcare providers, social media may show an essential part in satisfying their requirements. Therefore, users may connect with those who share their observations about health problems including diabetes and high blood pressure on social networking sites like Twitter and Facebook. Healthcare professionals and patients can learn from others' experiences on social media sites regarding diabetes management. To improve patients' treatment and instruction, as well as to predict patients' stress and melancholy levels, they collect SMD such as drug analyses and expressive explanations from patients.

3.1.4 Webpages

Diabetes patients are intrigued regarding any harmful impact on Health, illnesses, and symptoms associated with a certain medication. There is a lot of material on such websites about negative pharmacological responses to great anti-diabetes medications. The suggested system picked these websites as its data sources. We searched for 1600 postings using the names of pharmaceuticals used to treat diabetes and high blood pressure, and then we searched for articles that only mentioned drugs consuming a keyword-based machine. The suggested system also used an automated web crawler to collect 25,000 operator reviews about medications.

Facebook: Internet-based social networking in the healthcare sector takes grown. To address their demands, patients interact with online communities. Patients can exchange data through platforms provided by organizations like the Diabetes Daily, American Diabetes Association, and Diabetes Health. Patients can comment on posts and spread them around. We used a Java client called RestFB and the Graph application programming interfaces (API) to retrieve information from Facebook sites. We can gather data from Facebook automatically thanks to the Graph API.

Twitter: To locate Tweet with data regarding diabetes, they utilized Twitter's REST API and Streaming API. Utilizing a variety of queries on the REST API, we were able to get the latest Tweets. The most precise diabetes-related phrases should be used in these inquiries to get the Tweets that are most pertinent to the topic. To do this, we created queries using keyword analysis of the Boolean algorithms AND and OR, such as patient AND for diabetes, patient AND for hypertension, and patient AND for diabetes medicines. To create searches about diabetes, more than 30 keywords were employed. We used the aforementioned keywords-based searches to get 300,000 tweets concerning diabetic patients, treatments, medications, and symptoms.

3.2. Pre-processing of Min-max Normalization

Data normalization is a pre-processing method used to apply organization or clustering algorithms that primarily categorize healthcare information. However, choosing the normalizing method and frequency is regarded as an essential phase during the pre-processing stage.

Min-max normalization: This provides one of the most often used methods for normalizing data, where values for the feature under consideration are typically converted to new, smaller values within a predetermined range. It is understood that min-max normalization preserves every connection in the data under consideration. According to the following equation [10], every value in the feature under consideration is mapped to a new normalized value.

$$v' = \frac{v - min_A}{max_A - min_A}(new - max_A - new - min_A) + new - min_A \quad (1)$$

Where v′ is the fresh normalized value, The starting value for the specified feature is v, maxA is the highest possible value for the specified feature A, For the specified feature A, minA is the lowest value, while new_maxA and new_minA are the highest and lowest values for the newly taken into account range.

3.3. Feature Extraction by using Linear Discriminant Analysis (LDA)

This method uses LDA for feature extraction techniques to categorize healthcare monitoring. The discriminant analysis creates a combination of various factors that are independent and focuses on the relationship between several independent variables and a category-dependent variable. This type of multivariate analysis may assess how well any compound variable distinguishes between several prior categories of individuals and can also provide a model of classification for forecasting the collective status of fresh information. Assuming that the explanation elements are generally prevalent with identical covariance matrices, linear discriminant analysis may be used to determine which groups have similar characteristics. The LDA is represented by

$$LDF = b_0 + b_1 x_{i1} + b_1 x_{i2} + \cdots + b_k x_{ik} += bX, \quad (2)$$

where bj is the amount of the jth coefficient, j = 1, ..., k, and x_{ij} is the amount of the ith instance of the jth predictor. The fact that such composite averages of squares include both the variance and the variability of every variable is a crucial feature. The discriminant coefficients may be computed in both individualized and normalized forms, however, they are, compared to those in regression, less useful. The grouping criterion constructed on Fisher's discriminant functions is as follows, Assuming there are two groups, $\overline{x_1} and \overline{x_2}$ are the averages for each category, and S is the pooled covariance matrix.

$$X_i \in \begin{cases} group\ 1,\ if\ y = (\overline{x_1} - \overline{x_2})' S^{-1} X_i \\ \quad \geq \frac{1}{2} (\overline{x_1} - \overline{x_2})' S^{-1} (\overline{x_1} - \overline{x_2}), \\ group\ 2,\ if\ y = (\overline{x_1} - \overline{x_2})' S^{-1} X_i \\ \quad < \frac{1}{2} (\overline{x_1} - \overline{x_2})' S^{-1} (\overline{x_1} - \overline{x_2}). \end{cases} \quad (3)$$

3.4. Fuzzy Binary Temporal Long Short-Term Memory (FBTLSTM)

FBTLSTM uses binary encoding methods to express time in addition to fuzzy logic. The process of binary encoding converts time series data into binary vectors, where each bit represents a discrete time interval. For jobs requiring sequential data processing, this encoding might be significant since it allows the network to collect and alter temporal connections between distinct time steps directly. FBTLSTM incorporates fuzzy logic and binary encoding strategies to improve the temporal learning capacities of the LSTM architecture. The goal of FBTLSTM is to improve the model's capacity for learning and reasoning about temporal trends in series by integrating fuzzy logic with binary encoding and the LSTM architecture. For problems like time series prediction, sequence creation, and temporal pattern recognition where fuzzy or ambiguous temporal links are important, it offers a flexible and strong framework.

In the FBTLSTM technique, the lower and upper bound, and approach standards need to be educated. The building of the FBTLSTM technique considering the input lower limit of $\left\{\left(v_{j,}e_j^{KSq}\right), j = 1,2,\ldots,M\right\}$approach$\left\{\left(v_{j,}e_j^{NKq}\right), j = 1,2,\ldots,N\right\}$and the upper bound of $\left\{\left(v_{j,}e_j^{WKq}\right), j = 1,2,\ldots,M\right\}$ correspondingly, can be shown in the following way

$$e_{KSq}(v_j) = \Upsilon_j^K = P_{Kj} \otimes tan\ g(d_{Kj}) \quad (4)$$

$$e_{KSq}(v_j) = \Upsilon_j^N = P_{Nj} \otimes tan\ g(d_{Nj}) \quad (5)$$

$$e_{WSq}(v_j) = \Upsilon_j^W = P_{Wj} \otimes tan\ g(d_{Wj}) \quad (6)$$

The main layer of the FBTLSTM uses the tanh activation function, and the fuzzy output data are stored in FBT long-term memory.

Input fuzzy gate:

$$\widetilde{J_J} = \left(\sigma\left(U_{vKJ}^S v_{Kj} + U_{gKJ}^S g_K(j-1) + a_{Kj}\right)\sigma\left(U_{vNJ}^S v_{Nj} + U_{gNJ}^S g_N(j-1) + a_{Nj}\right), \left(U_{vWJ}^S v_{Wj} + U_{gKJ}^S g_W(j-1) + a_{Wj}\right)\right) \quad (7)$$

Forget gate of fuzzy:

$$\widetilde{e_J} = \left(\sigma\left(U_{vKe}^S v_{Kj} + U_{gKe}^S g_K(j-1) + a_{Kj}\right)\sigma\left(U_{vNe}^S v_{Nj} + U_{gNe}^S g_N(j-1) + a_{Ne}\right), \left(U_{vWe0}^S v_{We} + U_{gKe}^S g_W(j-1) + a_{We}\right)\right) \quad (8)$$

Output gate of fuzzy:

$$\widetilde{p_J} = \left(\sigma\left(U_{vKp}^S v_{Kj} + U_{gKp}^S g_K(j-1) + a_{Kj}\right)\sigma\left(U_{vNp}^S v_{Nj} + U_{gNp}^S g_N(j-1) + a_{Np}\right), \left(U_{vWp}^S v_{Wp} + U_{gKp}^S g_W(j-1) + a_{Wp}\right)\right) \quad (9)$$

Signals from neurons to cells:

$$\widetilde{h_J} = \left(\sigma\left(U_{vKh}^S v_{Kj} + U_{gKh}^S g_K(j-1) + a_{Kj}\right)\sigma\left(U_{vNh}^S v_{Nj} + U_{gNh}^S g_N(j-1) + a_{Nh}\right), \left(U_{vWh}^S v_{Wh} + U_{gKh}^S g_W(j-1) + a_{Wh}\right)\right) \quad (10)$$

Where, $\widetilde{U_{vJ}} =, \left(U_{vKJ}^S, U_{vNJ}^S, U_{vWJ}^S\right)$, $\widetilde{U_{ve}} =, \left(U_{vKe}^S, U_{vNe}^S, U_{vWe}^S\right)$

$\widetilde{U_{vp}} =, \left(U_{vKp}^S, U_{vNp}^S, U_{vWp}^S\right)$ and $\widetilde{U_{vh}} = \left(U_{vKh}^S, U_{vNh}^S, U_{vVh}^S\right)$ Every of the 4 layers' fuzzy weight matrices is utilized to link them to the fuzzy input vector, and the fuzzy weight matrices relate to the fuzzy short-term state $\widetilde{g_{J-1} =}, a_j, a_e, a_p, a_h,$ $\widetilde{a_J \equiv} (a_{KJ,} a_{NJ,} a_{WJ,})$, $\widetilde{a_e \equiv} (a_{KJ,} a_{NJ,} a_{WJ,})$, $\widetilde{a_p \equiv}, (a_{Kp}, a_{Np}, a_{Wp})$and $\widetilde{a_h \equiv}, (a_{Kh}, a_{Nh}, a_{Wh})$. At last, they arrive at the following methods for determining both the long- and short-term states, fuzzy long-term outlook:

$$\widetilde{d_J} = \widetilde{e_J} \times \widetilde{d_{J-1}} + \widetilde{I_J} \times \widetilde{h_J} \quad (11)$$

$$\widetilde{Y_J} = \widetilde{h_J} = \widetilde{p_J} \times tanh(\widetilde{d_J}) \quad (12)$$

Additionally, this FBTLSTM incorporates the stochastic optimization-based adaptive moment estimation optimization approach to find the ideal FBTLSTM parameters. The practical demonstration of the Adam optimization method demonstrates that convergence conforms to the predictions of the theoretical analysis. Based on the Adam optimization approach, the suggested FBTLSTM may achieve reliable performance. The FBTLSTM has a maximum of 250 epochs, .005 gradient thresholds, 1, 125 learn rate drop periods, and 0.2 learn rate drop factors.

4. Performance Analysis

4.1. Results

In this part, the suggested system's effectiveness is evaluated. The performance indicators used for assessment are accuracy, precision, recall, f-measure, and efficiency. K-Nearest Neighbor (KNN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) are the existing methods used for comparison.

4.1.1. Accuracy

A difference between the outcome and the true number is caused by inadequate precision. The percentage of actual outcomes reveals how balanced the data is overall. The accuracy of healthcare monitoring refers to the way different elements of a patient's health are measured and tracked by various healthcare systems, equipment, and technology. Doctors need to have accurate information to make educated diagnoses and give patients the treatment they require. Accuracy is assessed using an equation (13).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

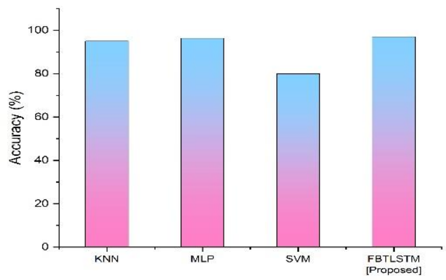

Fig.2. Accuracy comparisons between the suggested and current approaches

igure. 2 demonstrates the comparable values for the accuracy measures. When compared to existing methods like K-NN, which has an accuracy rate of 95%, MLP, which has an accuracy rate of 96.3%, and SVM, which has an accuracy rate of 80%, the recommended method's FBTLSTM value is 97%. The proposed approach, therefore, has the greatest accuracy rate. Table 1 displays the proposed method's accuracy.

Table 1. Comparison of Accuracy

Methods	*Accuracy (%)*
KNN	95
MLP	96.3
SVM	80
FBTLSTM [Proposed]	97

4.1.2. Precision

The most crucial standard for accuracy is precision, it is clearly defined the percentage of accurate case classification in all illustrations of predictively optimistic information. Precise and reliable evaluations and measurements are what we mean when we talk about precision in the field of healthcare monitoring. It's an essential part of healthcare monitoring since it determines the trustworthiness of the data used to make decisions. Equation (14) is used to compute the precision.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (14)$$

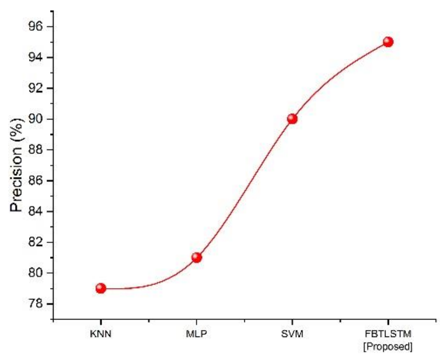

Fig.3. Precision comparisons between the suggested and current approaches

Figure. 3 displays the comparable values for the precision measures. When compared to existing methods like K-NN, which has a precision rate of 79%, MLP, which has a precision rate of 81%, and SVM, which has a precision rate of 90%, the recommended method's FBTLSTM value is 95%. The suggested FBTLSTM performs well in categorizing healthcare monitoring and has higher precision than other methods. Table 2 shows the precision of the suggested method is contrasted with the existing methods.

Table 2. Comparison of Precision

Methods	*Precision (%)*
KNN	79
MLP	81
SVM	90
FBTLSTM [Proposed]	95

4.1.3. Recall

The potential of a model to classify each significant example within a data collection is known as recall. The percentage of True Positive is divided by the sum of True Positive and False Negative is how it is statistically defined. In the region of medical procedures and illness prediction models, recall is an essential factor for measuring the success of healthcare systems. An accurate positive rate indicates that a test or model can accurately identify a sufficient percentage of true positives. The recall is calculated using equation (15).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (15)$$

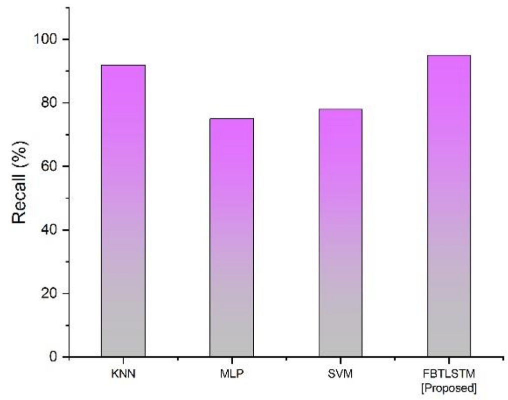

Fig.4. Recall comparisons between the suggested and current approaches

Figure. 4 demonstrates the comparable values for the Recall measures. K-NN has a recall rate of 92%, whereas MLP and SVM both have recall rates of 75% and 78%, respectively, the recommended method's FBTLSTM value is 92%. The suggested FBTLSTM performs well in categorizing healthcare monitoring and has higher Recall than other methods. Table 3, the recall of the suggested method is contrasted with the existing methods.

Table 3. Comparison of Recall

Methods	*Recall (%)*
KNN	92
MLP	75
SVM	78
FBTLSTM [Proposed]	95
KNN	92

4.1.4. Efficiency

Efficiency in healthcare monitoring refers to the enhancement of procedures and tools used to monitor and control the state of the health of people or groups. Healthcare monitoring seeks to increase effectiveness to raise patient outcomes, raise treatment quality, and lower costs. Figure 5 suggests the optimal performance of the suggested method. It shows the suggested approach is more efficient than the existing approach. Table 4 displays the proposed method's Efficiency.

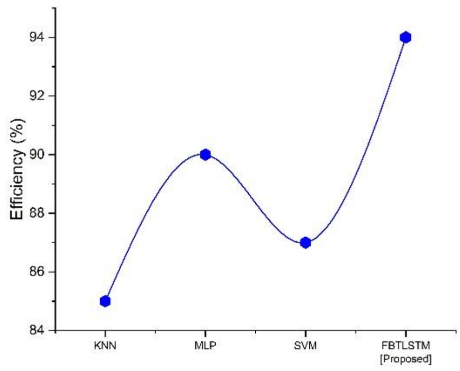

Fig.5. Efficiency comparisons between the suggested and current approaches

Table 4. Comparison of Efficiency

Methods	*Efficiency (%)*
KNN	85
MLP	90
SVM	87
FBTLSTM [Proposed]	94

4.1.4. F1-Score

F1-Score is a statistical metric used to evaluate the performance of a binary classification model by combining precision and recall. The harmonic mean of accuracy and recall is another name for it. Recall evaluates how successfully every model recognizes all positive instances out of all real positive occurrences, whereas precision measures how correctly a model predicts positive instances out of all cases it predicted as positive. The harmonic mean of accuracy and recall is used to calculate F1-Score, with the following formula (10)

$$F1 = \frac{2 * (precision * recall)}{(precision+recall)} \quad (16)$$

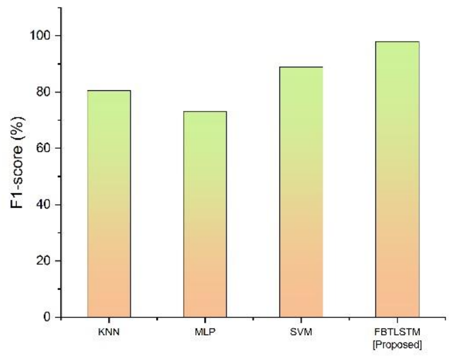

Fig.6. F1-Score comparisons between the suggested and current approaches

Figure. 6 demonstrates the comparable values for the F-measure measures. When compared to existing methods like K-NN, which has an F-measure rate of 80.5%, MLP, which has an F-measure rate of 73%, and SVM, which has an F-measure rate of 89%, the recommended method's FBTLSTM value is 98%. The suggested FBTLSTM performs well in categorizing healthcare monitoring and has a higher F-measure than other methods. Table 5 displays the proposed method's F1-Score.

Table 5. Comparison of F1-Score

Methods	*F1-Score (%)*
KNN	80.5
MLP	73
SVM	89
FBTLSTM [Proposed]	98

5. Conclusion and Future Work

In conclusion, the incorporation of WS and social media information into an automated healthcare monitoring infrastructure has the potential to completely change the way healthcare is delivered by allowing individualized, proactive, and data-driven treatment. Accepting these developments may enable people to take charge of their health, increase the ability of medical professionals to make decisions, and ultimately improve patient outcomes. WS and SMP are essential for the creation of a unique method for collecting patient data for efficient healthcare monitoring. As a result, we introduced the Fuzzy Binary Temporal Long Short-Term Memory (FBTLSTM) for categorizing healthcare monitoring. Performance metrics like accuracy, precision, Recall, efficiency, and F-measure, are evaluated and compared with existing technologies like the K-Nearest Neighbor (K-NN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM). A promising method for certain kinds of analysis of time series occupations, FBTLSTM makes use of the strength of fuzzy binary operations to record and reason about ambiguous temporal connections. A mathematical system known as fuzzy logic addresses ambiguity and imprecision. It enables the processing and display of hazy and unclear information. Fuzzy logic has been effectively used in a variety of fields, including decision-making, control systems, and pattern recognition. In applications involving sequential data, such as time series analysis, voice recognition, and natural language processing, LSTMs are often utilized. To improve performance, even more, creative approaches might be applied to the suggested system in further studies.

References

[1] Aldahiri, A., Alrashed, B., & Hussain, W. (2021). Trends in using IoT with machine learning in health prediction systems. Forecasting, 3(1), 181-206.

[2] Subasi, A., Khateeb, K., Brahimi, T., & Sarirete, A. (2020). Human activity recognition using machine learning methods in a smart healthcare environment. In Innovation in health informatics (pp. 123-144). Academic Press.

[3] J, V. ., Rajalakshmi, R. ., Gracewell, J. J. ., Suganthi, S., Kuppuchamy, R. ., & Ganesh, S. S. . (2023). Deep Featured Adaptive Dense Net Convolutional Neural Network Based Cardiac Risk Prediction in Big Data Healthcare Environment. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 219–229. https://doi.org/10.17762/ijritcc.v11i2s.6065

[4] Bokharaei Nia, M., Afshar Kazemi, M., Valmohammadi, C., & Abbaspour, G. (2021). Wearable IoT intelligent recommender framework for a smarter healthcare approach. Library Hi Tech.

[5] Comito, C., Falcone, D., & Forestiero, A. (2020, December). Integrating IoT and social media for smart health monitoring. In 2020 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT) (pp. 692-698). IEEE.

[6] Mamdiwar, S. D., Shakruwala, Z., Chadha, U., Srinivasan, K., & Chang, C. Y. (2021). Recent

advances in IoT-assisted wearable sensor systems for healthcare monitoring. Biosensors, 11(10), 372.

[7] Andreu-Perez, J., Leff, D. R., Ip, H. M., & Yang, G. Z. (2015). From wearable sensors to smart implants-–toward pervasive and personalized healthcare. IEEE Transactions on Biomedical Engineering, 62(12), 2750-2762.

[8] Kim, J., Campbell, A. S., de Ávila, B. E. F., & Wang, J. (2019). Wearable biosensors for healthcare monitoring. Nature Biotechnology, 37(4), 389-406.

[9] Azodo, I., Williams, R., Sheikh, A., & Cresswell, K. (2020). Opportunities and challenges surrounding the use of data from wearable sensor devices in health care: a qualitative interview study. Journal of medical Internet research, 22(10), e19542.

[10] Ghiasi, S., Zhu, T., Lu, P., Hagenah, J., Khanh, P. N. Q., Hao, N. V., ... & Clifton, D. A. (2022). Sepsis Mortality Prediction Using Wearable Monitoring in Low–Middle Income Countries. Sensors, 22(10), 3866.

[11] Gedam, S., & Paul, S. (2020, July). Automatic stress detection using wearable sensors and machine learning: A review. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-7). IEEE.

[12] Jayaraman, P. P., Forkan, A. R. M., Morshed, A., Haghighi, P. D., & Kang, Y. B. (2020). Healthcare 4.0: A review of frontiers in digital health. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(2), e1350.

[13] George, U. Z., Moon, K. S., & Lee, S. Q. (2021). Extraction and analysis of respiratory motion using a comprehensive wearable health monitoring system. Sensors, 21(4), 1393.

[14] Mohanta, B., Das, P., & Patnaik, S. (2019, May). Healthcare 5.0: A paradigm shift in digital healthcare system using artificial intelligence, IOT and 5G communication. In 2019 International conference on applied machine learning (ICAML) (pp. 191-196). IEEE.

[15] Ramesh, J., Aburukba, R., & Sagahyroon, A. (2021). A remote healthcare monitoring framework for diabetes prediction using machine learning. Healthcare Technology Letters, 8(3), 45-57.

[16] Awotunde, J. B., Ayoade, O. B., Ajamu, G. J., AbdulRaheem, M., & Oladipo, I. D. (2022). Internet of things and cloud activity monitoring systems for elderly healthcare. In Internet of Things for Human-Centered Design: Application to Elderly Healthcare (pp. 181-207). Singapore: Springer Nature Singapore.

[17] Jaber, M. M., Alameri, T., Ali, M. H., Alsyouf, A., Al-Bsheish, M., Aldhmadi, B. K., ... & Jarrar, M. T. (2022). Remotely monitoring COVID-19 patient health condition using metaheuristics convolute networks from IoT-based wearable device health data. Sensors, 22(3), 1205.

[18] Breteler, M. J., KleinJan, E. J., Dohmen, D. A., Leenen, L. P., van Hillegersberg, R., Ruurda, J. P., ... & Kalkman, C. J. (2020). Vital signs monitoring with wearable sensors in high-risk surgical patients: a clinical validation study. Anesthesiology, 132(3), 424-439.

[19] Ghazaly, N. M. . (2020). Secure Internet of Things Environment Based Blockchain Analysis. Research Journal of Computer Systems and Engineering, 1(2), 26:30. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/8

[20] Sharma, H. K., Taneja, S., Ahmed, E., & Patni, J. C. (2019, October). I-Doctor: an IoT based self patient's health monitoring system. In 2019 International Conference on Innovative Sustainable Computational Technologies (CISCT) (pp. 1-6). IEEE.

[21] Mbunge, E., Muchemwa, B., & Batani, J. (2021). Sensors and healthcare 5.0: transformative shift in virtual care through emerging digital health technologies. Global Health Journal, 5(4), 169-177.

[22] Jantawong, P., Jitpattanakul, A., & Mekruksavanich, S. (2021, August). Enhancement of human complex activity recognition using wearable sensors data with inceptiontime network. In 2021 2nd International Conference on Big Data Analytics and Practices (IBDAP) (pp. 12-16). IEEE.

[23] Ali, F., El-Sappagh, S., Islam, S. R., Ali, A., Attique, M., Imran, M., & Kwak, K. S. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. Future Generation Computer Systems, 114, 23-43.