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# Machine Learning–Based Classification Framework for Human Health Care Monitoring

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**Abstract:** The healthcare sector generates extensive patient and disease-related data, which, when integrated with artificial intelligence (AI), enables the discovery of latent disease patterns, personalized treatment planning, and condition prediction. Facial expression recognition is a key component in patient health assessment, supporting rapid emergency response. However, variations in posture, scale, occlusion, and illumination often degrade recognition accuracy. This work presents an enhanced facial expression recognition framework employing Local Binary Patterns (LBP) for robust feature extraction, coupled with Discrete Cosine Transformation (DCT) for frequency-domain representation. Three classifiers—Support Vector Machine (SVM), Recurrent Neural Network (RNN), and Naïve Bayes (NB)—are evaluated for integration into wearable health monitoring systems. Experimental validation on standard benchmark datasets demonstrates that the proposed method achieves superior recognition accuracy compared to existing approaches, offering improved reliability for real-time healthcare monitoring applications.

**Keywords:** Machine Learning; Image Processing; Patient, Human; Health Monitoring; Local Binary Patterns

## 1. Introduction

Health is defined as a state of complete well-being, encompassing not only the absence of disease but also physical, mental, and social wellness [1]. It is a fundamental prerequisite for improving quality of life [2]. However, the global health crisis has been exacerbated by factors such as inadequate healthcare infrastructure [3], persistent disparities between rural and urban regions, and shortages of medical practitioners and nursing staff during critical periods [4].

Unhealthy lifestyles are influenced by multiple factors, including irregular dietary habits, poor nutrition, environmental pollution, lack of suitable employment, job dissatisfaction [5], and psychological stress, all of which contribute to serious health complications [6]. Due to the demands of modern life, many individuals have limited time to prioritize their health, increasing the risk of various medical conditions [7]. Continuous patient monitoring by a physician is often impractical [8], and self-monitoring without professional guidance remains challenging [9]. Additional obstacles, such as long waiting times, travel requirements, and exposure to unsanitary environments, further hinder timely medical attention [10].

To address these challenges, the healthcare industry has increasingly focused on home-based healthcare services, allowing patients to undergo medical assessments in the comfort of their own homes [11]. Machine learning (ML) has emerged as a powerful tool in this context, enabling the diagnosis of diseases and the development of personalized treatment plans [12]. ML-based methods are particularly useful for segmenting or detecting abnormalities in medical data, with suspicious regions classified as malignant or benign [13]. This process can be approached as a supervised classification task—first, by labeling each pixel as potentially abnormal [14], and second, by further analyzing and categorizing identified anomalies as hazardous or non-hazardous [15].

Remote health monitoring systems enable physicians in metropolitan areas to consult with patients in rural locations [16], acting as a platform to connect patients and healthcare providers [17]. These systems collect various health parameters—such as heart rate, ECG, blood pressure, temperature, and fall detection data [18]—which are transmitted via Internet Protocol to analytical applications [19]. They can display real-time patient footage through a web interface, utilize cloud-based ML models to detect emergencies [20], and promptly alert physicians and emergency services [21]. Data can be monitored locally or globally via secure web platforms [40]. However, many commercially available monitoring solutions are costly, even for the measurement of a single health parameter [22]. In hospital settings, each patient is typically connected to multiple medical devices, such as ECG, EEG, and wearable sensors [23]. These devices record the patient's health status and transmit the data in standardized formats to internal servers [24]. The collected data is analyzed using pre-trained models built from historical medical records [25], and may be securely stored and shared via cloud platforms for authorized use by medical professionals.

The main contributions of this research are as follows:

- Train and evaluate data to forecast the patient's health status during the therapy.
- Improved communication between the physician and the patient and targeted the efficient transfer of health data through the health monitoring system through cognitive technology.
- The local binary pattern (LBP) technique design for implementing an intelligent patient health tracking system is presented. Determining diseases by minimizing visits, hospitalization, and diagnostic tests is aimed at creating monitoring systems.

The rest of the paper is discussed as section 2 is a literature survey for healthcare monitoring. Section 3 presents the local binary patterns method with machine learning, and section 4 is defined for experimental analysis of healthcare monitoring. Section 5 is the conclusion.

## 2. Related work on health monitoring systems based on ML

This section represents most of related work such as Kumar et al. [26] proposed the mental information transmission technique (CDTM) for patient wellbeing related information to be followed, recorded, and sent. The main need is information transmission when the wellbeing status is basic and can be distinguished from the information bundle data. They determined the future wellbeing of most connected patients because of their ongoing medical conditions utilizing a stochastic forecasted portrayal.

Huifeng et al. [27] presented wearable sensors because of the web of things (WS-IoT) method for sports individuals' constant wellbeing observing framework. The program aimed to define medical and performance health clinics and enable athletes to return to various athletic areas using the technologies. With wearable monitoring devices, health information was gathered, and training records were tracked. Khan et al. [28] explained that health monitoring and prediction systems, mainly when remotely situated patients, are crucial in saving many lives. The adaptive neuro-fuzzy inference (ANFIS) approach provides an internet-based health monitoring system to predict heart disease. Imran et al. [29] explored the internet of things as founded on various biomedical sensing appliances for health surveillance purposes. Elderly Patients' Medical Monitoring technique in the home, ambulance, and hospital environments (CLHE) closed-loop healthcare environment was proposed. This system identified and notified authorities based on biological sensors of worsening situations for more rapid action. Harimoorthy et al. [30] mentioned patient information and disease-related information are included in the healthcare sector statistics. A vast amount of data was offered to analyze the hidden patterns of the disease to give the patient individualized care and predict the disease. RBKM (Radial Bias Kernel Method) was utilized. Abdulameer et al. [31] demonstrated the prototype of an automated system that guarantees continuous control over health parameters and prevents all illnesses from repeated trips to the hospital to patients. The web of technical things can be installed in hospitals, and huge amounts of data can be collected and stored in the internet database. Valsalan et al. [32] explained that the IoT must be viewed as a realistic option, particularly in medical monitoring, for remote value tracking. IoT allows the secure inside of the cloud data for individual prosperity parameters and reduced stays in the hospital for traditional regular tests, particularly crucial for monitoring health and diagnosing sickness by a doctor at any distance.

Singh [33] examined the stage of IoT technology that can considerably influence human health services and related markets. People and other things can be tracked thanks to high-speed internet connections and powerful sensor technologies. Networked sensor devices for live settings enabled information to collect body temperature, blood pressure, and sugar level to evaluate the patient's physical and mental status. Chatrati et al. [34] referenced that distant patient observation may be feasible for diabetic and circulatory strain patients. A blend of ward choices and AI approaches were utilized to foresee hypertension and diabetes. The goal was to gauge hypertension and diabetes with the patient's glucose and circulatory strain information. Mohammed et al. [35] explained a relatively novel issue had been medical rehabilitation which plays a significant role in health care for patients, especially the elderly infected with chronic illnesses. These have been significant and advantageous in health monitoring systems such as medical devices, drug controls, and implementation techniques, including rehabilitation systems. Naik et al. [36] examined that IoT established an interconnected network and was subsequently acknowledged as renewing technology. With this technology, the healthcare industry was improved. Cardiovascular health issues, pulmonary failure, and cardiovascular conditions increased daily. The doctor could therefore monitor the patient's health continually without interacting physically. Souri et al. [37] proposed health surveillance of an IoT-based student to control key indicators and identify student biological and behavioral changes using intelligent student care technology. The proposed system's conceptual paradigm considered three levels for data collection utilizing biomedical sensors and calculating the necessary data based on biological markers for the student health monitoring system.

The above works have unique pros and cons that are still unaddressed. In this research, Local binary patterns (LBP) have been suggested to remotely monitor numerous physiological indicators to allow elderly and chronically sick people to live comfortably with monitoring their health. AI calculations handle colossal patient information measures and concentrate altogether characteristic, recently covered up, and significantly pertinent information data in the e-wellbeing framework.

### 3. Local binary patterns based on human health monitoring system of machine learning

Artificial intelligence technologies have been essential components of the latest advancements in medical imaging. They have mainly been machine (deep) learning approaches. They are previously utilized or considered so that most tasks, such as image reconstruction, processing, analysis, and predictive modeling, are tackled. This study includes the introduction and definition of local binary patterns and discusses how approaches in this area can be used with a particular focus on medical imaging applications.

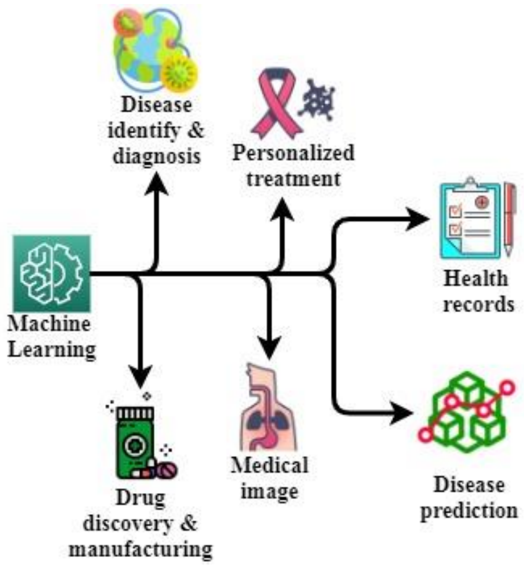



**Figure 1:** Machine Learning in Healthcare

Figure 1 says manually tricky to diagnose illnesses, and machine training plays a vital role in identifying, monitoring, and preventing disease in patients. The discovery or production of a novel medicine can be costly and long-lasting since many substances are tested, and only one outcome can prove effective. The checked images of the patients can now uncover slight irregularities, bringing about a legitimate finding by subject matter experts. Specialists can give individual patients with fitted treatment to meet their precise necessities. They want to get experiences from monster informational indexes and apply them to make individual patients sound. It is tedious and tiring to keep up with exceptional wellbeing records consistently. After these huge undertakings, it is a field where machine training has entered to save time, exertion, and cash to keep wellbeing information. ML techniques, for example, counterfeit brain organizations, empower us to participate and expect anything from minor ailments to persistent extreme irresistible circumstances.

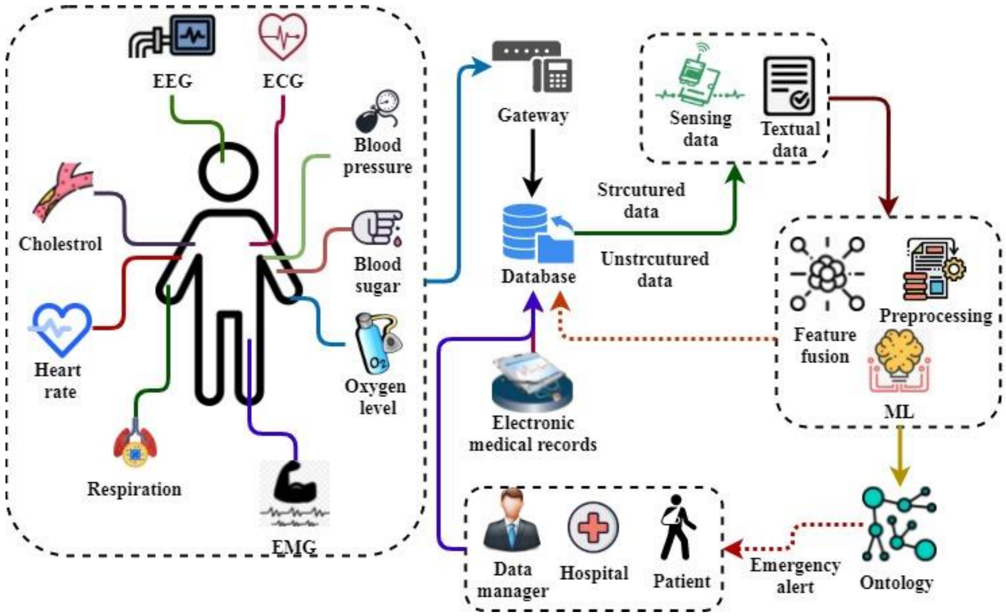



**Figure 2:** Human healthcare monitoring (HHM) structure of prediction of disease

Figure 2 shows the structure is separated into several levels so that the information base for each phase in the proposed system can be fully described. Finally, the design and ontology used by the HHM for predicting cardiac diseases and recommending dietary programs and activities are provided for the deeper-learning model ensemble. The system is based on medical sensors that gather physiological data, internally or externally, such as electric cardiograms (ECG), electroencephalography (EEGs), electromyograms (EMG), heart rates, blood pressure (BP), respiration, and blood sugar. Electronic medical records (EMRs) contain reports from observers, medical history, smoking history, diabetes, and extensive clinical examinations. After the cardiac patient senses the data, the proposed system transfers the data to the gateway devices. Various instruments can be utilized as a gateway for collecting and transmitting sensed data. The detected data and EMRs are safely retained in a database termed big medical data. To anticipate heart illnesses, use a health prediction and a diagnostic engine based on structured and unstructured data. The retrieved characteristics are merged with the suggested fusion system, including structured and unstructured data. The data is pre-processed using techniques of data mining. This stage involves filtering the data, standardization, proper data mining selection, and conditional probability function weighting. The data are sent to a machine study classification trained on a heart disease dataset to forecast heart disease. The ontology is utilized to propose a diet or activities based on the patient's health.

$$H = \frac{1}{3}\sqrt{D\left(A^2 - \frac{s}{2}\right)} - \sum(L_0 + m) \tag{1}$$

Equation (1) denotes D structured data H for maximum database storage, A for error rate, s for patient's oxygen level, L for accuracy, m for medical history. Ontology is used to suggest a health-based diet plan or activities and the prediction of health conditions, and an engine for predicting cardiac illness based on structured and unstructured data collected.

$$P_d = \oint 2\cot^{-1}\left(\frac{X}{t-2} * \frac{1}{2}\right) + \sum_0^\infty J^2(z) \tag{2}$$

Equation (2) says P_d is the patient's observation, cot^(-1) is the trigonometric function of respiration rate, X for lab reports, t for many emergency patients, J for sensed data, z for normalized data value. The idea of medical terms and the link between them is described by Ontology in medicine, thereby facilitating the communication of medical information. Ontological analyses are linked to the possibility that modeling mistakes might impair the quality of outcomes.

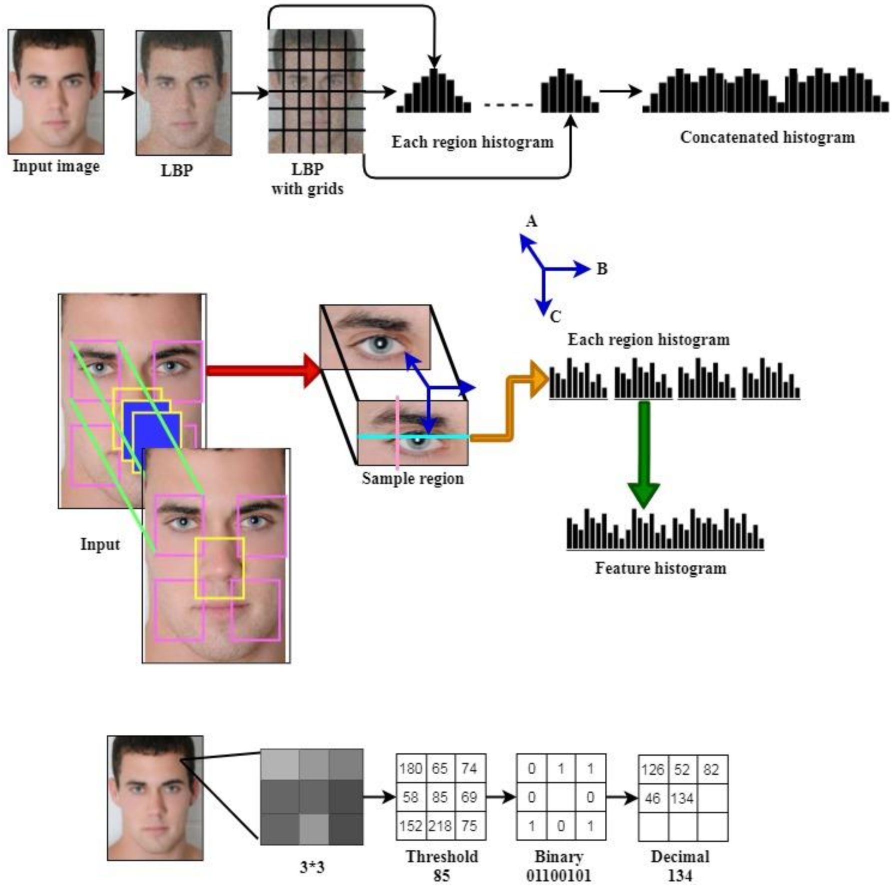



**Figure 3:** Histogram formations of local binary patterns (LBP)

Figure 3 mentioned that the central concept for developing the LBP operator was to provide two complementary measurements for the two-dimensional surface textures of the input image [38]: spatial domains and the gray size. The LBP operator creates labels for image pixels by switching to a binary number, the 3 X 3 area of each pixel with the center value. That is, possible as a texture description with a histogram of those 28 = 256 distinct labels. Together with a primary local contrast measure, this operator showed excellent performance in unchecked texture segmentation. Many related techniques to texture and color texture segmentation have subsequently been developed. In effect, this histogram has a visual description on three different locality levels: LBP histogram labels provide pixel-level pattern information, labeling across a small region for regional information is summarized, and regional histograms for a global visual description. It is important to remember that areas do not need to be rectangular when utilizing histogram-based techniques. Both have to be the same size or form and don't have to cover the entire image. Some overlapping areas can be found.

$$M = \prod_0^7 \alpha_n - (Z + V^2) * \exp \sigma^2 \quad (3)$$

The equation (3) explained M for histogram match, α is the mathematical function of the pixel of the image, n for some regions, Z is the resolution, V for image fusion, exp σ is the exponential function of the face.

Each histogram measures the incidence of all 256 potential LBP codes in the block. After the training and test phases, the number of bins necessary for describing the histogram can be established by the resultant accuracy. When all 256 containers are employed, a lengthy histogram descriptor results, which has significant computer demands and storage needs.

$$c(i) = \int_{-\infty}^{\infty} (\frac{1}{2} - G_z) * (\frac{(N-1)}{2}) + \sin\frac{1}{\beta} \quad (4)$$

Equation (4) says c(i) care of region, G is the time taken for identifying the area, z for binary level, N for several threshold values, sin is the trigonometric function of gray level, β is the mathematical function of the histogram.

The histogram method successfully exhibits three levels: pixel-level information in the individual LBP code, regional-level information in histograms, and global descriptions in the concatenated regional histograms. Consequently, histograms encrypt features in a small display, making an item sturdier and more illuminated.

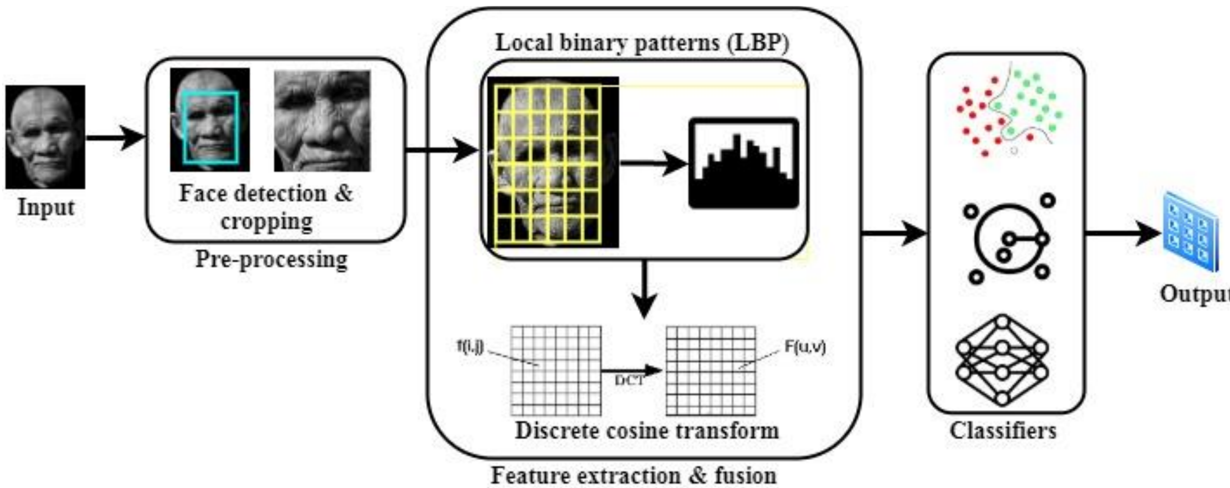



**Figure 4:** Proposed local binary patterns architecture with machine learning

Figure 4 describes new patch-based multiple LBP designer descriptions in the suggested approach. The image display is calculated utilizing these descriptors from the local patch values and, using small binary strings, encodes local micro-texture features surrounding each pixel. The input images in [38] are pre-proceeded to recognize the face from the complete image using the Viola-Jones method. LBP is a very effective texture operator that recognizes and views each pixel by calculating the proximity of each pixel as a binary integer. The LBP texture manager has been an essential technique for several applications because of its discriminating and computing ease. A unifying method can be considered to be the typical heterogeneous statistical and structural paradigm for texture analysis. DCT is a method that represents a image as a sum of sine waves of different magnitudes and frequencies. DCT-2 technology is used in the proposed strategy to extract features. DCT is applied to an input image in two-dimensional (2-D"), transforming it into DCT matrix coefficients with the image input. The LBP codes are produced, and characteristics are retrieved by the DCT in each feature engineering technique independently. The elements are combined to create a function vector. A matrix and some functions, such as 64 (8 to 8), are used as input for the zigzag function and return a single-dimensional array of the zigzag scanning results.

$$Q_2 = \sum_1^7 (S_i + y^3) * \log(c - \frac{1}{\delta^2}) \quad (5)$$

Equation (5) explains Q for the output of the digital image, S for a database of medical, i for total classifiers, y for image radius, c for polar coordinates, δ is the mathematical function of the original image, log for the logarithmic function of uniform image regions. The local binary pattern is a compelling image texture descriptor that thresholds the next pixels based on the current pixel value. The LBP descriptors effectively capture local space patterns and the grey contrast in a image.

$$g = \int_{-\infty}^{\infty} \frac{1}{2} \sqrt{(\varphi - R_o)} + \lim_{\infty} \left(1 + \frac{\sigma}{w^3}\right)^2 \qquad (6)$$

Equation (6) denotes g for total grey level images, φ is the mathematical function of facial expressions, R for facial activity, lim is the mathematical of binary pattern variant, w for correlation images, σ is the mathematical function of input images.

In explaining medical images, LBP has recently been shown to be beneficial. In the LBP, image volumes are described when the system searches the corresponding pieces for a search image. Facial recognition is the most significant safety available in healthcare to safeguard patient information and authenticate identification while enabling physicians to securely exchange patient information with other physicians for a faster recovery and a unique treatment for the patient.

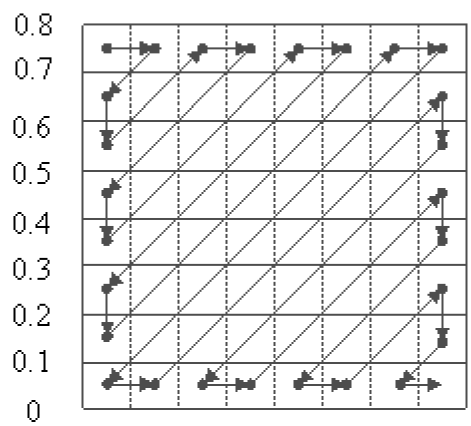



**Figure 5:** Zigzag formation of the input image for DCT

In the feature engineering stage, followed by the feature merge, the functional vectors of each dataset will be individually encoded and extracted. SVM, RNN, and NB classes are utilized to classify facial expressions using specified characteristics in Figure 5.

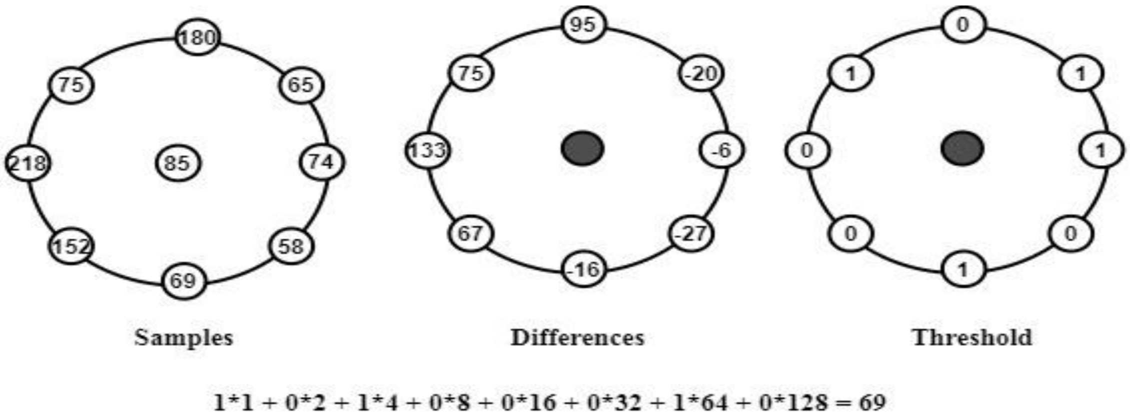



**Figure 6:** Computation level of LBP in machine learning

The LBP operator has been expanded to utilize regions of various sizes. In non-integer pixel coordination, circular districts with bilinear internal values allow for any pixel range and number. As an additional contrast metric, the greyscale variance of a neighborhood can be utilized. The pixel neighborhoods meaning sample points on the radius circle, must be marked as follows. See the LBP computation example in Figure 6.

The so-called unit patterns, which can be utilized to decrease the vector length and give a primary invariant rotation descriptor, can be added to the original operator. This development has led to a more common observation of specific binary patterns in texture images. If the binary design has two-bit size transitions of 0-1 or the other way around, a local binary pattern will be uniform if the bit pattern is circled.

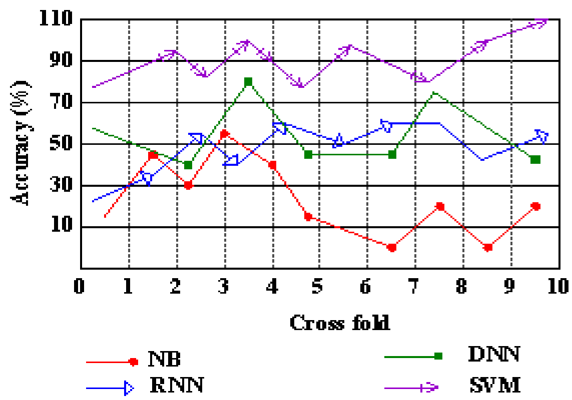



**Figure 7:** Accuracy comparing various classifiers of LBP face detection

The classifiers used were different classification approaches SVM, NB, RNN, and DNN. The experimental findings show that the classification algorithms are accurate. With 94.2 % accuracy, SVM has achieved the most outstanding performance in facial expression. Compared to other classifiers, the high accuracy of SVM is a significant distinction that makes it appropriate to monitor human health in real-time, as shown in Figure 7.

**Table 1:** Study of various ML techniques for the area under the curve

| Disease | NB | RNN | DNN | SVM |
|---|---|---|---|---|
| Thyroid | 80.0% | 62.35% | 82.4% | 92.07% |
| Cancer | 48.71% | 34.2% | 40.02% | 37.4% |
| Heart attack | 38.12% | 56.23% | 38.7% | 42.31% |
| Diabetes | 71.25% | 50.3% | 80.02% | 64.18% |
| Blood pressure | 58.68% | 43.1% | 51.6% | 57.29% |

Disease-wise comparative analysis of the area under the curve for different machine learning techniques are presented in Table 1 and below Figure 8 as a graphical representation of disease types.

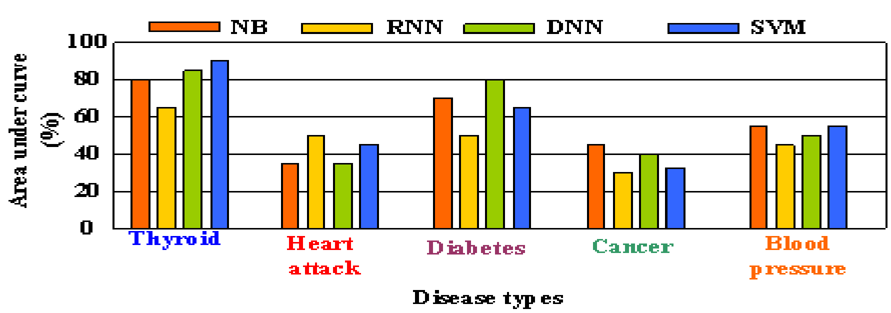


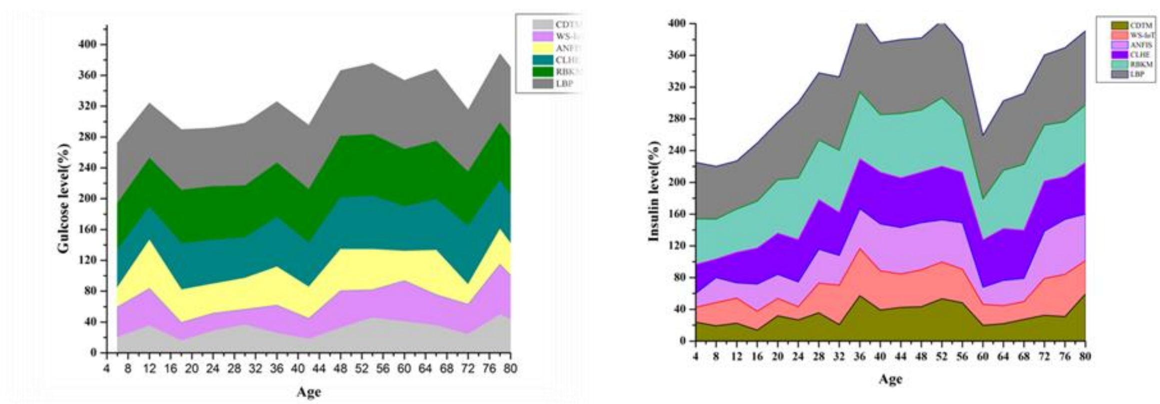

**Figure 8:** Different machine learning classifiers in the area under the curve of LBP

In the above Figure 8, results of the healthcare system using a few machine learning algorithms like Deep neural network (DNN), Navies Bayesian (NB), Support Vector Machine (SVM), and Recurrent neural network (RNN) are presented. These results are graphically shown in Fig. 8. SVM provides the highest area curve in thyroid rate of 92.07%; Heart attack samples comprise more area curved by RNN of 56.23%, and the diabetes detection rate highest of DNN method is 80.02%. Cancer provides good response in the region by NB classifier of 48.71%, finally for blood pressure ratio is higher than other techniques of NB is 58.68%.

## 4. Experimental analysis of HHM on ML with LBP

LBP is mainly utilized for categorization and illness prediction in healthcare monitoring. For categorization and illness prediction, many ML methods are available. This study studies and assesses several categorization methods for LBP and a monitoring system for human health. This study aims to explore the experimental outcomes of several classification algorithms used to categorize the data of various wearable sensors used to monitor multiple illnesses.

### *4.1 Prediction of age*

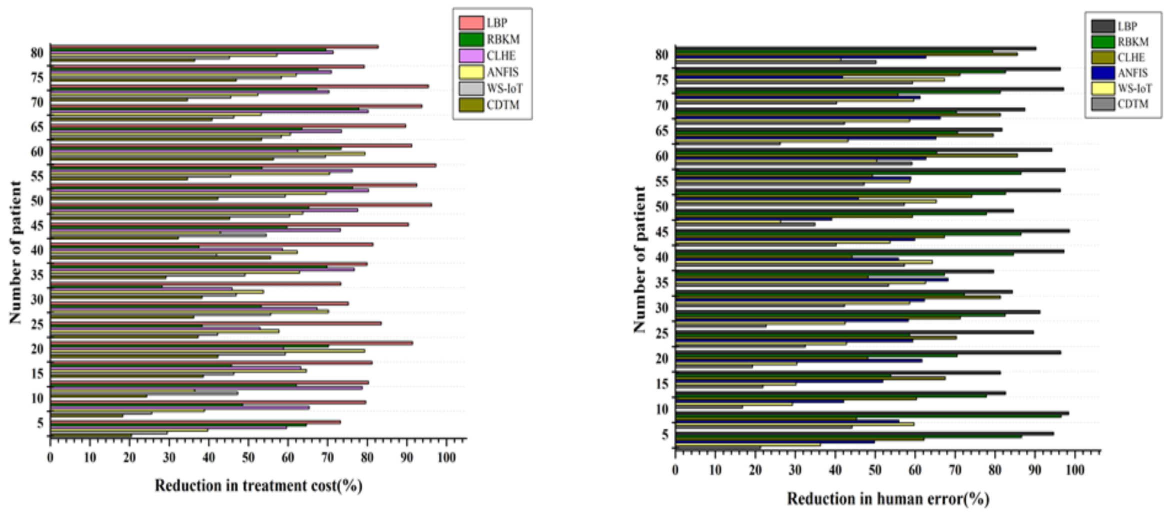



a) Gulcose level b) Insulin level

**Figure 9:** Prediction analysis with age

In Figure 9, prediction analysis with age is explained on data sets that the machine has educated to create whether or not a disease afflicts an individual. Machine learning technology is employed. The potential results justify the person at whatever age, and other probable factors that impact the origin of the illness are affected. For prediction analysis, two primary elements are considered: Age – level of glucose; age – human insulin. Insulin assists the body in making energy from glucose. It enables the body to store it later when the organism needs it in muscles, fat cells, and the liver.

### *4.2 Performance of machine learning*

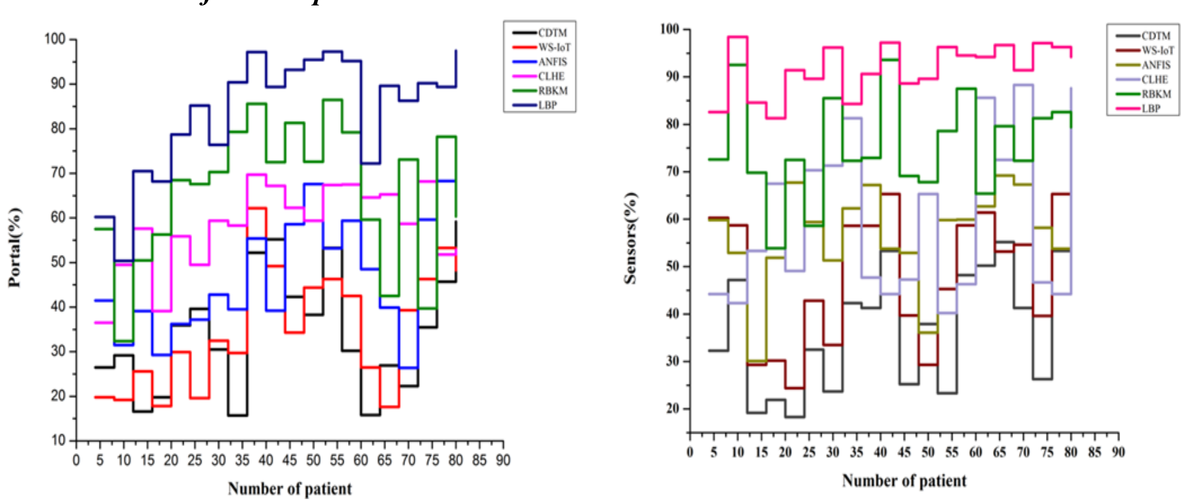



a) Reduction in treatment cost b) Reduction in human error

**Figure 10:** Performance analysis of machine learning classifiers

In Figure 10, the performance analysis of machine learning classifiers denotes the healthcare system provides patient follow-up 24/7. It can decrease unnecessary hospital visits, transport, and treatment costs. Doctors' advice can be provided through internet video streaming from home, and only patients can contact hospitals in urgent scenarios. In machine learning monitoring, information on physical health, such as blood pressure, sugar level, etc., is gathered precisely and depends on the sensor, which helps to reduce human mistakes.

### *4.3 Enhancement of disease prediction*

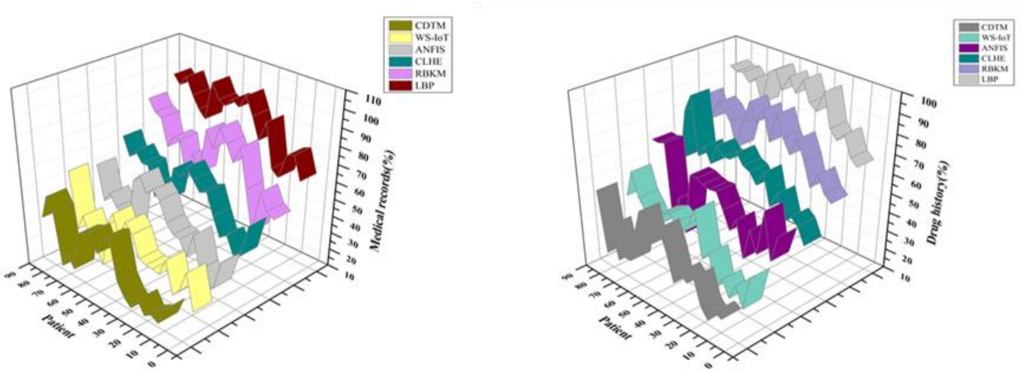



a) Portal b) Sensors

**Figure 11:** Disease prediction

In Figure 11, enhancement of disease prediction denotes disease prediction is made for specific diseases alone. This system anticipated the illness using the sensors and the machine learning portal. The sensors are implanted in the patient's body to monitor the body's temperature, heart rate, and blood pressure and provide data to the controller. It predicts the condition and diagnoses it. This emerging method assists with predicting, analyzing, and identifying a disease using data mining and portals on patient history. The machine learning portal is a means to recognize patient health.

### 4.4 Improvement of patient care

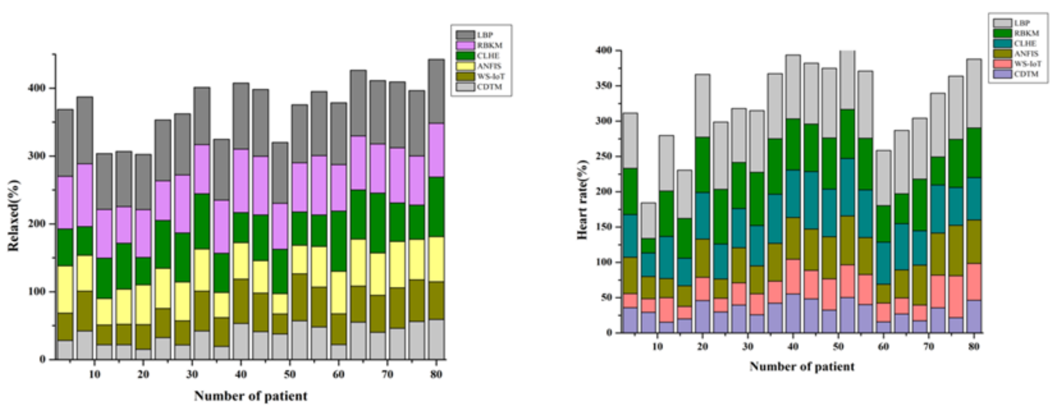



a) Medical records    b) Drug history

**Figure 12:** Patient care

In Figure 12, the improvement of patient care explains that healthcare professionals have access to correct patient information to get better medical attention. Electronic records can enhance the capacity to identify diseases, decrease medical problems, and improve the results of patients. The history of drugs is crucial to prevent mistakes in the prescription and subsequent dangers for patients. Detailed medication history is beneficial, aside from preventing prescription misconceptions in detecting drug-associated pathology or changes in clinical symptoms that might occur from drug therapy.

### 4.5 Patients' stress monitor




a) Relaxed    b) Heart rate

**Figure 13:** Patients' stress monitoring.

In Figure 13, patients' stress monitoring denotes the variability of the cardiac rate is one of the most solid, non-invasive stress response measurements because stress will immediately activate the neurological system, which primarily raises the cardiac rates of a patient. Relaxation can soothe the mind and relax the patients. Relaxation helps the patient's body breathe more slowly, lower blood pressure, and decrease heart rates. The response to peace is the reverse of stress. Finally, stress surveillance and prevention have a tremendous capacity for preventing and managing diseases and improving the patient's quality of life.

## 5. Conclusion

The proposed research uses an ensemble machine model for learning and the combination of local binary pattern techniques to enhance the accuracy of illness prediction and help identify the patient's facial expressions quickly and correctly. In addition, DCT has the feature extract capacity to address illustration problems, changes in size, large dimensions, noisy images, and more complexity of the texture-based characteristics; a multiple LBP descriptor approach based on the patch has been suggested. The technique proposes a prediction system that identifies and critically analyses the most significant risk variables in highly dimensional health data to forecast diseases precisely before developing. The proposed ensemble-deep learning model successfully addresses two distinct data sources and the performance of face-to-face and diseases. This proposed approach appropriately combines sensor data with derived features to create relevant data for the classification model. This novel technique discovers the optimal collection of parts and their uniqueness in prediction accuracy data sets. It can draw relevant characteristics from structured and unstructured data, and low-dimensional efficiency conveys these derived characteristics to improve the performance of illness prediction.

In a future study, data mining approaches will increase the performance of feature fusion to generate a more sophisticated dataset for diagnosing heart disease. In addition, new methods are created to reduce features to manage enormous amounts of health information and features. Finally, a more advanced way to remove unnecessary parts and handle missing data and noise is studied to obtain efficient outcomes.

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**Data Availability**: The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Conflicts of Interest:** No conflict of interest is stated by the author.

**Authors contributions.** Conceptualization, methodology, validation, writing—original draft preparation, writing—review and editing, visualization, supervision and project administration: SZK. The author had approved the final version.

**Declaration:**

**Ethics approval:** Not applicable

**Consent to participate**: Not applicable

**Consent to publish:** Not applicable

**Institutional Review Board Statement:** Not applicable.

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**Clinical trial number:** Not applicable

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