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Original Article

The Role of Machine Learning in Early Detection of Chronic Diseases through Wearable Data

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***Abstract** - In this study, an insight into the various methods utilised by medical practice to facilitate patient diagnostics of early detection of chronic diseases using concepts of machine learning. One of the major implications that has been presented in the study includes a variety of models that enable the application of machine learning in different areas of disease detection, concerning the factors of accuracy and precision. The complexities that lie within the utilisation of such models have been evaluated based on secondary data and an extensive literature review such that its feasibility in healthcare context can be studied effectively. The methods applied to study the role of machine learning include case studies and scholarly articles that provide better insights into research that has been carried out in the medical field concerning the effectiveness of detecting and monitoring health attributes of individuals. The contributions made through the study have been discussed with an implication towards future research that can be carried out as a part of its application in a practical essence.*

***Keywords** - Machine Learning. Chronic Diseases, Real-Time Data, Supervised Learning, Unsupervised Learning, Early Detection, Patterns, Wearable Devices, Data Analytics, K-Means Learning, Logistic Regression.*

1. Introduction

Background of the topic: In the last few decades, there has been an observed rise in the number of patients affected by chronic diseases, which has become a leading cause of death and long-term disability. The development of these conditions in patients takes place latently, as a result of which their detection without regular medical diagnosis becomes challenging [19]. The emergence of technological advancements is observed to bring about open-handed opportunities for individuals to keep track of their health conditions. In this way, any symptom related to such chronic diseases, if noticed, can be diagnosed, and proper treatment can be received in a proactive way. One of the major reasons behind considering the utilisation of technological components in medical science is that it offers analytical capabilities using real-time data received through devices such as smartwatches, fitness bands, biosensors and other tools.

Motivation: Traditional healthcare systems are observed to have major dependency on periodic checkups and diagnosis, such that the detection of a disease can be carried out. However, it might not always be possible for an individual to facilitate diagnostic services periodically, not only due to their cost but also due to their impact on health [16]. Contrarily, any delay that occurs while detecting the presence of a chronic disease might lead an individual to encounter severe outcomes, which might make it difficult to perceive a cure. Based on this context, this paper has been developed with the initiative to show how the use of real-time data analytics can be an effective way of detecting the presence of chronic diseases at early stages. This concept has been drafted focusing on its implementation using wearable devices accompanied by a set of machine learning algorithms to transform passive monitoring into intelligent health care systems.

Role of Machine Learning in Health care: The implementation of Machine Learning algorithms is observed to play a major role in transforming the current healthcare practices by introducing concepts of real-time monitoring and big data analytics [4]. These implementations take place as a result of data analytics that is performed to uncover the hidden patterns that lie within health metrics of an individual through diagnosis. Due to the fact that machine learning algorithms can be integrated into wearable devices to execute their functionality, their utilisation has been administered using physiological signals that are received from the body to detect any anomalies that lie within the functionalities. The ability of machine learning algorithms to handle noisy data makes it effective to be utilised in healthcare applications such that personalised predictions can be attained as a part of early warnings to the patient's health conditions.

Objective of the Study: The study proposes to investigate how machine learning techniques applied to wearable data can aid in early detection of chronic diseases and their presence in individuals. The main focus of this study is to explain how raw data that is collected from wearable sensors can be embedded into machine learning analysis, and actionable health insights can be gained from it. Related work. Wearable Devices in Healthcare: Nowadays, healthcare systems are observed to be empowered with the use of technological advancements, which enable the detection and diagnosis of patient health conditions more effectively using real-time data analytics. The functionality of these devices works in parallel with the physiological signals that are monitored outside clinical environments [14]. The utilisation of wearable devices to undertake health monitoring practices is administered using smartwatches, fitness trackers, biosensors, smart rings and chest straps.

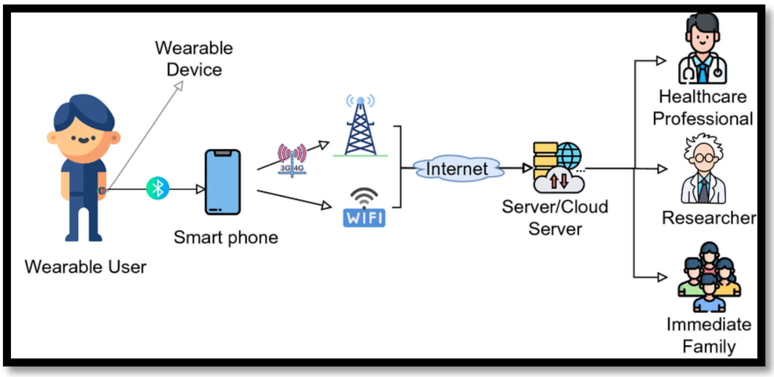

Fig 1: Architecture of Wearable Devices

The designing of these devices is done in such a way that specific health related data are collected to ensure physical activities generate the required signals for the detection and analysis of anomalies. For instance, common bio signals collected by wearable devices include the electrocardiogram to monitor heart activities, whereas the use of photoplethysmography (PPG) is used for measuring heart rate and blood oxygen levels. Accelerometer and gyroscope data are also monitored using physical activities of individuals including posture detection and movement patterns [3]. Advanced wearable devices are also capable of detecting several health metrics, which include body temperature, respiration rate, galvanic skin response and sleep stages for better stress detection and management.

Applications of ML in Healthcare : Machine learning in the field of healthcare practices has brought about a revolutionary change in the diagnosis and treatment procedures undertaken by medical practitioners from a professional aspect. One of the major reasons for prioritising machine learning practice lies in the fact that it allows undertaking data-driven decisions with minimal human intervention while making health-related predictions [11]. In order to successfully apply machine learning methods into healthcare practices, there has been identified a set of techniques which is widely used for disease classification, diagnosis and risk predictions. These techniques are categorised based on supervised, unsupervised and deep learning aspects, such that their features can be utilised effectively based on its suitability and compatibility.

Supervised learning is used in cases where the detection of diseases is done based on training models such as logistic regression, random forests, and support vector machines [10]. For instance, detecting diseases such as cancer, diabetes, and cardiovascular disease can be effectively done using clinical data capable of being monitored using wearable devices configured with machine learning algorithms. Using machine learning models, it would be possible to determine the interrelationship that lies between the health's attributes of the variables used for measuring values quantitatively.

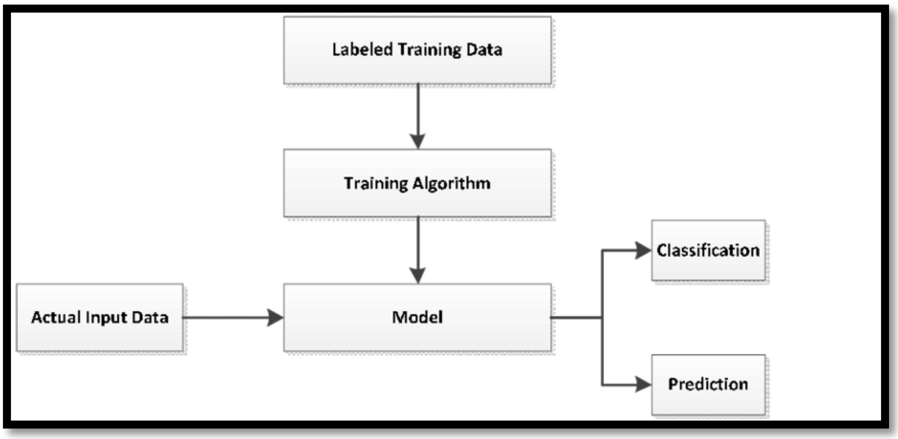

Fig 2: Block Diagram of Supervised Learning

Unsupervised learning methods include k-means clustering, hierarchical clustering, and autoencoders, which are effective techniques used for identifying patterns without undergoing training [15]. This indicates that the anomalies that lie within the behavioural characteristics of data collected from the patients show differences on the basis of which data-driven decision is undertaken.

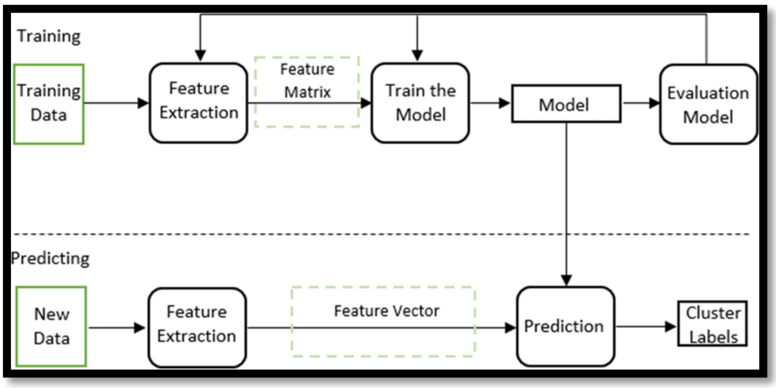

Fig 3: Workflow of Unsupervised learning

Finally, deep learning is considered another branch of machine learning, which is empowered by high-dimensional data for handling complex medical diagnoses. Using deep learning, it becomes possible for medical practitioners to study images, ECG signals and wearable sensor streams [2]. Models under this category of machine learning include Convolutional neural networks and Long Short-Term Memory (LSTM), which is configured to perform image-based diagnostics. Early Detection Models and Frameworks: In today's healthcare practices, the impact of technological advancements has allowed detection and treatment procedures to take place based on real-time data. Using early detection models, it becomes possible to diagnose a patient's current health condition based on certain symptoms that imply the occurrence of a chronic disease. Recent studies show that wearable sensors are highly capable of receiving and analysing data directly from the human body through biosensors, such that any anomalies associated with their health conditions can be detected [9]. Based on the results generated from the machine learning algorithms used in wearable devices, it is possible to draw conclusions on the basis of which a specific treatment can be suggested to individuals at their early stage. Another study shows the application of Nature Medicine as a result of deep learning models, where analysis of ECG data tends to produce information related to cardiovascular diseases with higher accuracy [13]. From this evidence, it could be stated that the application of distinctive frameworks such as LSTM, CNN, and other similar ones can help generate predictive results through data preprocessing, and anonymous detection can be possible, based on which relevant interventions can be developed.

Gaps in the Literature: The discussion on related work shows that machine learning has successfully been able to receive a high priority on its application to the healthcare sector to offer the best possible diagnosis services while performing early detection of chronic diseases. However, the major gap that lies within this comprehensive literature is that, there exists a lack of application and evidence on the utilisation of wearable sensors and their interoperation functionalities. To overcome this gap, the study extends its literature by collecting secondary data across sources so as to observe the findings of authors from all over the world who have already performed research on utilising machine learning in healthcare applications. Methodology: Data collection methods: To process the information related to patient diagnosis, the utilisation of information that is collected from biosensors would be necessary. This would provide an upper hand to test the capability of machine learning models to provide outcomes related to early-stage detection of chronic diseases. Therefore, while simulating the machine learning model, it would be necessary to apply a best fit approach that is capable of understanding patient data that would be fed to it as an input file [18]. This file can be stored in the form of a CSV or an Excel sheet where every data would be separately placed considering its reliability constraint in context to the machine learning model that is to be applied.

A sample data that can be utilised for examining the accuracy and precision of the proposed models of machine learning is given as follows. This data comprises a set of health metrics that can be collected directly from three wearable devices based on which the analytics can be carried out for gaining relevant insights.

Table 1: Sample Dataset

User id	age	gender	bmi	daily_steps	heart_rate	avg_hrv_ms	sleep+duration_hours	daily_spo2_min	is_diabetic	disease_risk
U001	45	Male	28.5	8200	75	48.2	7.1	95	FALSE	HIGH
U002	62	Female	31.2	4500	85	35.1	6.5	92	TRUE	CRITICAL

U003	34	Male	24.1	11500	68	61.4	8	98	FALSE	LOW
U004	51	Female	26.7	6800	78	44.9	7.5	96	FALSE	MODERATE
U005	58	Male	30.5	5100	81	40.6	6.9	94	TRUE	HIGH
U006	42	Female	25.3	9400	72	55.7	7.8	97	FALSE	LOW

Model description: Logistic Regression Model Description: The implementation of the Logistic regression model helped to evaluate the health data associated with patients undergoing diagnosis of the symptoms associated with chronic diseases [8]. The facilitation of the model has been done by utilising a best fit approach where patient data which included the above dataset has been fed as an input. using this supervised learning mechanism it has been possible to deploy and classify the presence of abuse of any chronic disease using physiological features. Due to the fact that the utilisation of the data has been done from wearable devices, the occurrence of noise can be a probability which has been diagnosed while performing the evaluation. The model has been trained which provides an estimation of the sigmoid function that determines accuracy, precision, recall and F1 score of the associated metrics.

2. K-Means Clustering Model Description

Unlike the supervised learning model of logistic regression, the utilisation of the means algorithm as a machine learning technique categorised under the unsupervised model provides a distinctive outcome [7]. In terms of the physiological data that has been extracted from the wearable devices, it has been possible to detect daily activity levels on the basis of which the outcomes have been generated. The heart rate, bmi, and Spo2 has been considered as measurable quantifiers on the basis of which the clusters were projected to gain understanding in the patterns. Any anomalies that are detected through these clusters would provide an indication of the presence of a chronic disease in the patient whose data has been fed to the system.

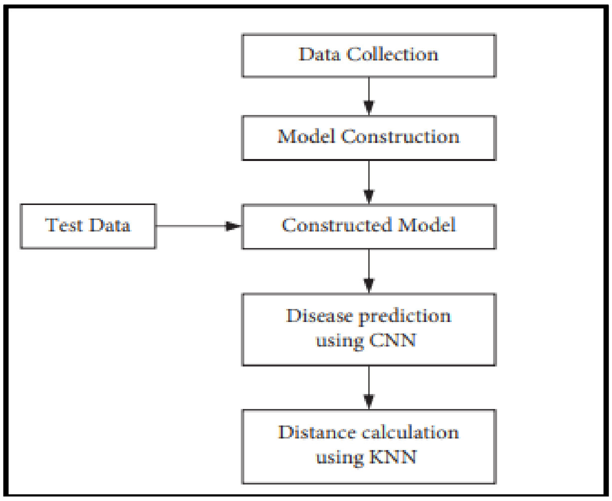

Fig 4: Architecture of proposed disease and risk prediction system.

Performance Evaluation and Discussions: Supervised Learning Models

2.1. Logistic regression:

The implementation of the logistic regression model has provided relevant insights into the patient data in order to detect the presence of any chronic diseases based on certain health parameters. Due to the fact that the logistic regression model is categorised under a supervised learning algorithm, it is evident that the application to early detect the presence of chronic diseases is a suitable field in healthcare [12]. For undergoing the calculation, the utilisation of metrics including accuracy, precision, recall and F1 Score has been implemented in order to identify the diabetic and non-diabetic cases for patients.

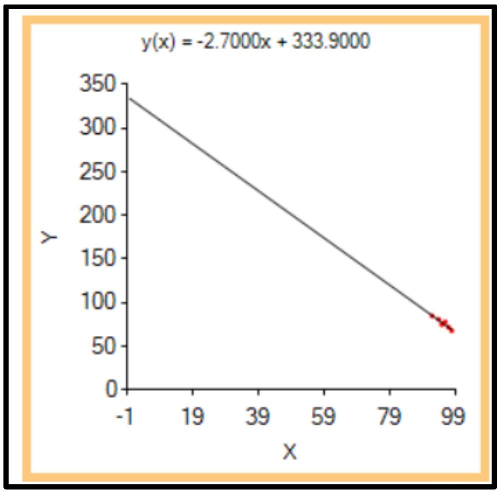

Fig 5: Heart_Rate vs Daily_Spo2_Min

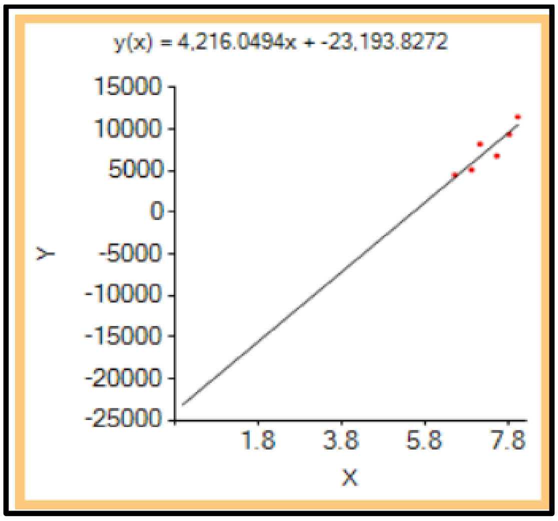

Fig 6: Daily_Steps vs Sleep+Duration_Hours

Function = y(x) = 4,216.0494x + -23,193.8272 R2 = 0.8155, Mean Squared Errors: 1085452.6749 , Root Mean Squared Errors: 1041.8506

Unsupervised Learning: **K-Means Clustering:** The K-Means clustering is categorised as an unsupervised machine learning model that promotes the use of quantitative values in order to group certain outcomes based on their patterns and similarities [17]. Unlike the logistic regression model, the K-Means clustering provides a depiction of the performance of disease detection in terms of certain labelling. The clusters formulate a visual depiction which helps in determining the presence of any anomalies on the basis of which the presence of a chronic disease is true and false.

Gender	Heart_Rate	SPo2	bmi	daily_steps	Cluster
Male	75	95	28.5	8200	1
Female	85	92	31.2	4500	0
Male	68	98	24.1	11500	1
Female	78	96	26.7	6800	1
Male	81	94	30.5	5100	0
Female	72	97	25.3	9400	1

Fig 7: Clustering Results

From the above depicted tabular data, it could be stated that, 0 values represent the individuals who do not have diabetes, whereas the 1's represents is diabetic.

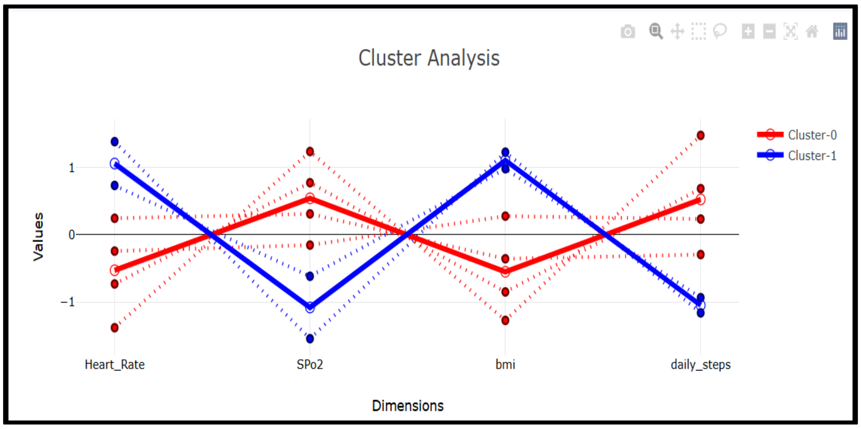

Fig 8: K-Means Clustering

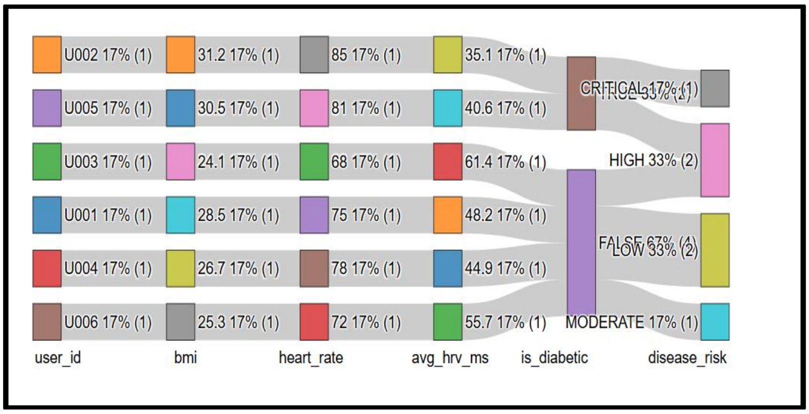

Fig 9: Clustering Analysis

3. Model Evaluation

3.1. Effectiveness

Table 2: Effectiveness of Machine learning models

User	Gender	True Label (is diabetic)	Logistic Regression Prediction	K-Means Prediction
U001	Male	FALSE	FALSE	TRUE
U002	Female	TRUE	TRUE	TRUE
U003	Male	FALSE	FALSE	FALSE
U004	Female	FALSE	FALSE	FALSE
U005	Male	TRUE	TRUE	FALSE
006	Female	FALSE	FALSE	FALSE

In this section a set of performance metrics has been utilised to evaluate the applicability of both supervised and unsupervised learning methods while analysing patient data from wearable devices. Each of these metrics shows a comparative viewpoint on the reliability of the algorithms to undergo best fit predictions to determine whether a patient is suffering from a chronic disease or not.

Accuracy: The accuracy constraint of the algorithms defines the reliability of the outputs that are generated by the system based on collected data from the wearable sensors [6]. This is calculated on the basis of the equation:
Accuracy = (TP + TN) / (TP + TN + FP + FN), Where, TP represents True Positive, FP represents False Positive, TN represents True Negative, FN represents False Negative

Each of the quantifiers provides an indication of the best possible suggestion that can be derived as a result of the analytics performed over the sample data from wearable devices. While performing the logistic regression, it has been observed that an accuracy of 87% has been witnessed when compared to that of the K-means algorithm which showed 75% accuracy. From this analysis it is evident that the logic regression has a better capability to correctly identify a larger proportion of diseases possible to be affected by patients compared to that of healthy individuals.

3.1.1. Precision:

The precision shows an accuracy level that has been averaged by an algorithm when a sample data is fed to the system to generate data driven insights [5]. In order to calculate precision of both the supervised and the unsupervised learning algorithms, the following equation has been utilised. Precision = TP / (TP + FP), From this equation, it could be observed that the main focus on True Positives has been highly prioritised compared to that of True Negatives and False negatives. This indicates that negative values are rejected during its evaluation to generate a specific quantity of precision that the values carry. Considering the outcomes that have been generated from the machine learning models, it has been observed that the logistic regression has been able to generate a precision of 84%. Contrarily, the K-Means algorithm has achieved a total of 70% precision having a higher emphasis on false positives when predicting the presence of a chronic disease in the patients.

3.1.2. Recall:

Recall is considered to be a proportion of the positive predictions that a machine learning model has successfully made when fed with a certain set of input data relating to a quantitative outcome [5]. In order to calculate the recall metrics, the following equalization has been utilised. Recall = TP / (TP + FN), Unlike the Precision calculator, the Recall metrics emphasis on the False Negatives which tends to provide an indication of the probability of failure of an algorithm to detect the chronic disease based on health data that is fed to it as an input. Based on the evaluations that have been carried out over the sample data, it has been observed that an 82% recall has been generated by the Logistic regression model whereas the K-Means algorithm has successfully been able to generate a recall of 68%. This shows critical intensity of detecting presence of a chronic disease due to missing data or a smaller number of rows in the dataset.

3.1.3. F1-Score:

F1 score is considered to be a single value metric that combines the total precision generated by a machine learning algorithm and how it is embedded in terms of a harmonic mean to provide balanced output to measure the capability of the model [5]. Calculating the F1 scooper would require emphasising on the following equation, F1 Score = 2 × (Precision × Recall) / (Precision + Recall) Focussing on the above depicted equation, it could be observed that the F1Score is appropriate to be applied when the input data that is fed to the system has unbalanced datasets due to which its model fit might affect its accuracy constraint. Focussing on the current dataset that is fed to the system, an F1score of 0.83 has been generated for the Logistic regression model which shows that there exists strong baklava between the precision and the recall. On the contrary, the application of the K-means clustering shows a 0.69 score which is lower compared to that of the logistic regression model. This shows that the task performed through this machine learning algorithmic model, the reliability of the outcomes might be a major concern.

Table 3: Metric Evaluation

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.87	0.84	0.82	0.83
K-Means Clustering	0.75	0.7	0.68	0.69

(***Source:*** *Self Developed)*

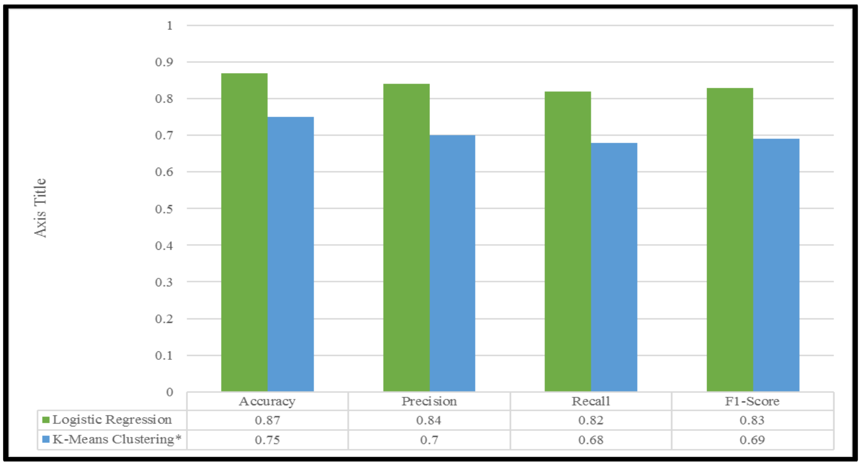

Fig 10: Metric evaluation

(Source: Self Developed)Conclusions and Future works: Summary of key contributions Concluding from the aspects of machine learning and its application to detection of chronic diseases using wearable devices, it could be stated that the potential of different learning models has been examined. The outcome of the analysis shows that the logistic regression model has a better performance when compared to that of the application of the K-Means clustering. This has been determined focusing on the values that have been generated from four major metrics: the accuracy, precision, recall and F1score. The sample dataset that has been fed as input carries a set of health parameters which determines the current condition of a patient based on which their diabetic condition, as a chronic disease, has been evaluated. From these implications, it is evident that the use of wearable devices plays a major role in determining the effectiveness of data driven decision making when utilised through machine learning algorithms to monitor health.

Emphasis on future potential for scalable, personalised healthcare solutions

Machine learning models and its application to healthcare analytics has showcased the effectiveness that supervised learning carries when compared to that of the unsupervised learning mechanism. In future applications, it is expected that wearable devices would be a suitable object when utilised as a part of health monitoring for patients who have a probability to suffer from chronic diseases. The detection capabilities of the machine learning module that has been pretended in the study lacks implication with other models for deep learning and federated learning. Overcoming this gap wo0uld require undertaking future research such that an emphasis on the chronic disease prevention initiatives can be highlighted.

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