IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 11, Issue 10, October 2024 https://www.ijirae.com/archives

The Investigation of Machine Learning and Deep Learning Classification of Internet of Things (IoT) Enabled Medical Devices

Shaikh Abdul Hannan
Assistant Professor, Faculty of Computing and Information,
AlBaha University, AlBaha, Kingdom of Saudi Arabia
abdulhannan05@gmail.com

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.11/Issue10/OCAE10083
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.11/Issue10/OCAE10083
Received:01,October 2024|Revised: 10,October 2024 |Accepted: 18, October 2024 | Published Online: 28, October 2024.
https://www.ijirae.com/volumes/Vol11/iss-10/04.OCAE10083.pdf
Article Citation: Shaikh(2024), The Investigation of Machine Learning And Deep Learning Classification of Internet of Things (IoT) Enabled Medical Devices. IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 11, Issue 10 of 2024 pages 787-793
Doi:>https://doi.org/10.26562/ijirae.2024.v1110.04
BibTeX Key Shaikh@2024Investigation

Abstract: The present cross-sectional, quantitative study investigates the classification capabilities of ML and DL in processing data from IoT-enabled medical devices: heart rate variability (HRV), blood pressure, blood glucose levels, and physical activity in patients with diabetes and cardiovascular diseases. Eight patients from AIIMS, New Delhi participated in this study. In the current investigation, two types of measurements are taken into consideration: cardiovascular measures and diabetes management metrics, which include BMI, blood pressure, blood glucose, physical activity, and HRV. The outcomes showed a positive association with blood glucose level and age (0.55), negative correlation between blood glucose and physical activity (-0.68), which had significant significance towards exercising importance in diabetes management. Blood glucose correlated moderately favorably with BMI with 0.45, while age and BMI correlated at 0.32. These results show how ML and DL techniques can improve the interpretation of complex health parameters from IoT-enabled devices to better manage patients and develop specific healthcare plans in chronic diseases.
Keywords: Machine Learning, Deep Learning, Classification, Internet of Things, (IoT) Enabled Medical Devices.

INTRODUCTION

A revolutionary change in healthcare technology in the form of explorations into ML and DL classification techniques for IoT-enabled medical devices (Al-Garadi, 2020). The study bridges the gap between data analytics and clinical practice. The volume of health-related data has exponentially increased with more integration of IoT-based wearable sensors and system remote monitoring support in healthcare platforms. There are abundant data; this leads to large opportunities as well as obstacles, which in turn call for sophisticated analytical techniques in extracting useful insights in such a regard (Bzai, 2022). For example, ML and DL have developed even stronger tools that will analyze large datasets and find very complex patterns they will guide judgments at a clinical level to improve the care of the patient. It is crucial for the performance of any IoT-enabled medical devices because it utilizes a number of statistical and computational techniques to learn from data. For instance, ML algorithms can classify and interpret data from wearables such as smartwatches, sleep patterns, physical activity, and heart rate (Chen, 2020). With this information, the health care providers can intervene more aptly and at the right time by being aware of trends in patient behavior and overall health. Moreover, with the early detection of health conditions, machine learning can even enhance the predictive capabilities of analytics to encourage the proactive care of patients (Deperlioglu, 2020). Algorithms can predict blood glucose levels for the future based on the previous records of diabetes patients and alert the patients and physicians to take preventive actions.

The truly promising evaluation of unstructured data is done with deep learning-the more advanced subset of machine learning that uses a multi-layered neural network, especially in medical imaging (Elhanashi, 2023). Algorithms for deep learning can analyze pictures in images produced by CT and MRI and X-rays with amazing precision. This allows radiologists to find anomalies, such as tumors or fractures that the human eye could easily miss. This feature has an effect of making it possible to have earlier time from diagnosis to treatment in the radiology department, since the process is made simpler and more accurate diagnoses occur (Ferrag, 2021). Secondly, deep learning can be employed for natural language processing applications wherein clinical notes and even patient records can be examined to bring out useful information about the effectiveness of the treatment as well as patient results. The integration of ML and DL with IoT-enabled medical equipment supports personalized medicine, which is seen beyond just data analysis (Ge, 2021). These algorithms can provide individualized treatment plans and health recommendations using specific patient data.

For example, an IoT-enabled cardiac monitoring device may make use of machine learning algorithms to predict most likely arrhythmias based on the heart rhythm patterns that are individual to a patient. This allows for tailored treatments that yield improved health outcomes for patients (Hameed, 2021). While the patient benefits from this tailored approach, it also ensures the health systems are maximally utilized by reducing unneeded admissions as well as treatments. IoT, ML, and DL also aid the development of intelligent health systems with characteristics such as automatic reporting and real-time monitoring of health. These devices will deliver continuous monitoring of chronic diseases so that patients can notice any significant changes in their health conditions right away. For example, IoT-blood pressure-monitoring devices would alert doctors immediately when the readings cross certain limits, thus enabling fast clinical intervention (Iranpak, 2021). This extent of automation and interconnectivity saves health care providers from much workload, allowing them to allocate their time to more demanding clinical responsibilities and ensure prompt care to patients in situations requiring it.

This area of study has the future of fully transforming the landscape of health care provision in its wake. In the context of ML/DL classification techniques for IoT-enabled medical equipment, benefits include better health outcomes, earlier disease detection, and more effective treatment regimens (Jayalaxmi, 2022). It also fosters interdisciplinary knowledge from data scientists, physicians, and engineers toward increasingly more complex models and systems that can adapt to the demands of a changing health care landscape. Therefore, time will only tell how these technologies can be maximally used for the benefit of both patients and providers to get over some of the problems plaguing the industry, including issues of privacy of data, transparency of algorithms, and integration with current healthcare infrastructures as the field develops. As such, research in ML and DL concerning IoT-enabled medical devices is purely fundamental and critical work whose findings will determine the future health care scenario and not a mere academic exercise.

1.1. Research Objectives

- To examine how blood pressure readings in individuals with cardiovascular diseases relate to heart rate variability (HRV) data obtained from Internet of Things (IoT)-enabled wearable devices.
- To assess how diabetes patients' blood glucose levels and physical activity data from Internet of Things devices correlate with one another.

2. LITERATURE REVIEW

Khanna et al. (2023) they showcased a novel method for processing biological electrocardiogram (ECG) data using deep learning in a distributed Internet of Things network for healthcare diagnostics(Khanna, 2023). According to the study, this combination will lead to better diagnostic precision with real-time disease detection and health monitoring capabilities. The authors in this study attempted to enhance the model's deep learning capacity to classify heart diseases by using a hybrid model for interpreting the ECG readings. According to their finding, this framework will facilitate the remote monitoring of patients besides the early detection and revolutionize patient care within a smart environment of healthcare.

Liu et al. (2021) it has done an exhaustive analysis of the machine learning-based methods that can identify and detect IoT devices (Liu, 2021). This study emphasizes the big role that machine learning plays in handling data coming from the Internet of Things for healthcare applications. The authors indicate that there is a dire need for strong algorithms that can detect and classify IoT devices across various health scenarios since they classify different machine learning approaches based on application scenarios. Liu et al. conduct a literature review bringing up the issues of data security and diversity in devices as challenges. Apart from these, they also propose a future research agenda that will focus on the issues that need to be dealt with while handling the integration of IoTs into intelligent healthcare systems.

Mansour et al. (2021) the authors investigated a disease diagnosis model for AI-IoT powered smart healthcare systems(Mansour, 2021). The suggested strategy is data processing from IoT devices through machine learning algorithms, which allows for the efficient detection of disease and treatment plans according to the needs of patients. The authors discuss how predictive analytics in patient care is supported through the synergy of AI and IoT, strengthening diagnostic capacities as well. The paper discusses how well the architecture would help in managing chronic illnesses by combining data gathering, processing, and analysis in the architectural structure of the model. The real-time data processing part that adds to enhancing health outcomes is emphasized by the authors; while doing this, they underline the revolutionary potential these technologies hold in the health sector.

Nagarajan et al. (2021) a deep learning-based task scheduling system for the Internet of Health Things was demonstrated in the context of sustainable smart cities, focusing on dealing with the multiple problems associated with health-related data produced by various devices in IoHT, where key issues are related to effective resource distribution with a focus on efficiency maximization and latency minimization (Nagarajan, 2021). Accordingly, scheduling tasks with deep learning-based policy prediction of job completion times and responsive resource allocation as an adaptive response to real-time analytics represents a completely novel framework proposed by the authors. Preliminary results from experimental setting show that their algorithm increases significantly both the rates of completion of tasks and reduces energy consumption, which is supportive of the sustainability goals of smart cities.

This research study emphasizes how smart resource management is of extreme importance in raising the effectiveness of healthcare systems functioning within the urban setting. Oniani et al. (2021) this paper discussed how AI is changing medical systems and the Internet of Things, the revolutionary potentials an AI-driven healthcare innovation can bring, and the writers' going through a number of AI techniques including deep learning and machine learning, giving better data processing and analysis results for better patients' outcomes(Oniani, 2021).

They outline some case examples that demonstrate AI in domains such as disease detection, customized treatment plans, and remote patient monitoring in their literature review. Oniani supports interdisciplinary solutions that combine AI and IoT to yield intelligent medical systems that respond better to issues. He achieves this through the synthesis of already existing literature and provides insight into the opportunities as well as the problems AI poses in the IoT healthcare ecosystem.

Pan et al. (2020) developed a better CNN with the support of deep learning to predict the incidence of heart disease on the platform IoMT(Pan, 2020). As per their research, in order to predict the proper risk associated with heart disease with up-to-date accuracy, the developed work depends on huge datasets via the health monitoring equipment and deep learning algorithms are utilized to analyze these.

A hybrid model was proposed by combining CNN with traditional machine learning algorithms for better prediction accuracy and robustness. This paper has shown that the proposed model is better than the present prediction techniques. It also suggests that AI-assisted IoMT solutions could significantly hasten early diagnosis and treatment of cardiac problems. The reason behind this work as to how contemporary data analytics enhances the health care decision-making process has been well brought out.

Rodrigues et al. (2020) presented a completely novel approach to the use of IoT devices, deep learning, and transfer learning for classification in skin lesion (Rodrigues, 2020). Their work allows for better accuracy in skin lesion diagnosis by the incorporation of IoT-enabling sensors and pre-trained deep learning models. The authors underscored the proof of concept regarding the efficiency of transfer learning, which amalgamates knowledge gathered from large sets of data with sparse data to enhance performance when performing classification tasks. Their proposed technology allows remote monitoring and diagnosis of skin diseases, which means they can treat the patient in good time. The results show great promise as the combination of IoT with deep learning represents one of the best approaches toward dermatological applications, perhaps yielding significant improvements in diagnostics accuracy.

Souri et al. (2020) a novel machine learning-based health monitoring model specifically tailored to detect health problems among students in an Internet of Things setting has been proposed by the authors(Souri, 2020). The framework proposed by the authors is based on machine learning algorithms that monitor and diagnose various health problems through the collection of health data via wearable technology. Based on the results, it is observed that the model is accurate in identifying the most frequent health issues students' face, thus contributing to early intervention and improved management of their health. Thus, the primary need that the study highlights is the provision and deployment of AI-driven solutions within classrooms in order to track and assess the health levels of these students.

Tan et al. (2023) their focus was on using wearable health devices with 5G in monitoring cardiovascular activity in real time from COVID-19 patients (Tan, 2023). The researchers applied deep learning algorithms to enable the understanding of data that would be acquired by wearable sensors as well as make possible effective cardiovascular health monitoring. According to the authors, high-speed connectivity is needed not only to maintain patient data but also to send quick warnings and interventions. The results of these authors were very explicit in that the method proposed really improves the monitoring of patients, especially during the times of the COVID-19 pandemic, where real-time health data is critical for effective care and treatment.

Ullah and Mahmoud (2021) they discussed designing and deploying deep learning for IoT network anomaly detection (Ullah, 2021). The research addresses the increasing security risk currently present within internet of things environments, especially when health related sensitive information is exchanged. The authors improved the security of health care information by proposing a deep learning architecture that can be used to deploy anomaly detection within the network. As the findings of the research go, the model ought to be able to detect suspicious activity reliably enough, thus providing an important level of security given the integration sweeping the healthcare world.

3. RESEARCH METHODOLOGY

3.1. Research Design

The research adopted a quantitative method to examine the relationship between diabetes management metrics and cardiovascular metrics from IoT-enabled medical devices (Veeramakali, 2021). A cross-sectional approach was taken in this study by collecting data from a sample of eight patients diagnosed with diseases related to diabetes and cardiovascular disease. Patients were engaged from the All India Institute of Medical Sciences, which is a prestigious hospital known for sophisticated medical technologies with IoT. Cardiology and endocrinology are the medical specialties covered here.

3.2. Data Collection

Patients who consented were able to have their data collected for one month. The age, medical history was documented in all patients (Wu, 2023). Besides, measurements of physiological parameters, including blood glucose, HRV, systolic and diastolic blood pressure, steps/day physical activity, and body mass index, were reported. This dataset uses IoT-enabled wearables to capture the signals of HRV and blood pressure values. Connected glucose meters and fitness trackers are used for the activity measures and blood glucose monitoring. The information is arranged into two datasets, one being the IoT Diabetes Glucose Activity Dataset and the Cardiovascular Metrics Dataset.

3.3. Ethical Consideration

Institutional Review Board, AIIMS, New Delhi gave ethical clearance. All subjects gave their informed consent before their inclusion in the study (Xu, 2023). Assurance to the participant regarding data privacy and the unrestricted right to withdraw at any point was given. The rights and welfare of all participants were assured, as the study met the ethical criteria of the Declaration of Helsinki.

3.4. Statistical Analysis

The data collected had to be processed, statistical software was used to analyze them (Yue, 2021). Descriptive statistics were conducted on physiological and demographic data on patients for the purpose of summarizing them, which enabled the making of a brief description of sample characteristics. Besides, a correlation analysis was carried out to consider the relationship between age, BMI, blood glucose levels, and the levels of physical activity. In this case, Pearson's correlation coefficients were calculated to establish the direction and strength of these relationships (Zhou, 2020). All statistical tests were conducted at a significance level of $p < 0.05$ so that the results had a good deal of reliability and were highly significant. A correlation matrix, involving results of correlation analysis, made easy one to understand how variables under study interacted with one another.

4. RESULT AND DISCUSSION

The tables and figures contain some of the key diabetic and cardiovascular-related metrics for a group of patients outlining general health status and corresponding problems. The measures presented here related to cardiovascular measures appear in Table 1 and include patients who range between 48 and 63 years of age. The heart rate variability values produce various ranges of autonomic modulation between 35 and 60 ms. The results suggest a wide spectrum of blood pressure regulation like the systolic values ranging between 125 mmHg to 160 mmHg, and the diastolic values range from 78 mmHg to 100 mmHg. BMI values reported herein are mixed of people with average and excessive weight, ranging from 24.8 kg/m² to 32.1 kg/m². Table 2 explaining the IoT Diabetes Glucose Activity Dataset, shows the blood glucose levels for the patients under investigation that range between 130 mg/dL and 200 mg/dL, and the degree of their physical activity that ranged between 3,000 and 11,000 steps per day. Patient 4, who has the highest blood glucose and lowest activity, is a nice illustration of how the results are interpreted in a manner that those whose glucose levels were higher in the sample often report levels of physical activity that are lower. Table 3's correlation analysis reveals a moderate positive relationship between blood glucose level and age, where older persons have the tendency to have higher glucose level. Exercise is highly important in the management of diabetes because there is a high negative correlation of blood glucose level with exercise at -0.68. There is also a small positive correlation of 0.45 between the BMI and the blood glucose levels, which mean those with higher BMIs might also have higher levels of blood glucose. Lastly, a close interrelationship among age, physical activity, and metabolic health underscores the importance of monitoring all these parameters during patient care. The association between age and BMI was of 0.32, indicating that aged patients tend to have higher values of BMI.

Table 1: Cardiovascular Metrics

Patient Number	Age	HRV (ms)	Systolic BP (mmHg)	Diastolic BP (mmHg)	BMI (kg/m²)
1	55	45	135	85	27.5
2	60	52	145	90	30.2
3	48	60	130	80	24.8
4	63	38	150	95	32.1
5	50	49	140	85	29.3
6	57	55	125	78	28.4
7	62	35	160	100	31
8	49	58	132	82	25.6

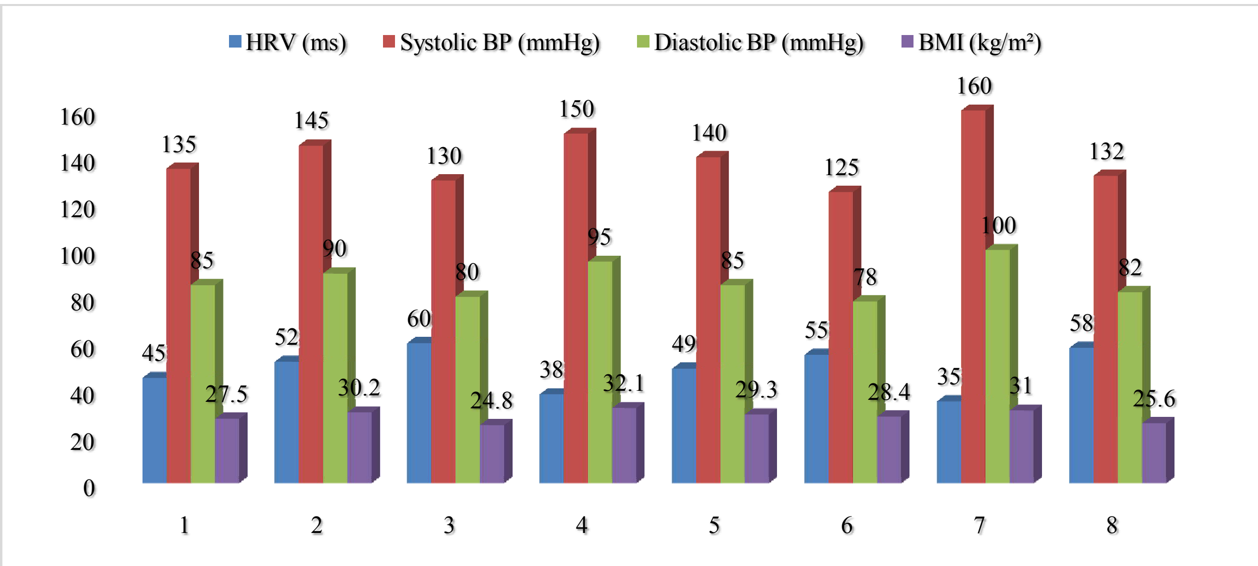

Figure 1: Cardiovascular Metrics

Table 1 Summary of the eight patients' cardiovascular measurements, including BMI and both systolic and diastolic BP, HRV, and age. Patient's ages range from 48 to 63 years. HRV ranges between 35 and 60 ms.

Differences in the diastolic blood pressure readings lie between 78 mmHg and 100 mmHg, and in the measurements of systolic blood pressure from 125 mmHg to 160 mmHg, showing that each of the patients has a different level of control over their blood pressure levels. The variation also remains in BMI values that lie between 24.8 kg/m2 and 32.1 kg/m2. This means that some patients fall under the class of being overweight or obese, whereas others fall into the categories of normal weight.

Table 2: IoT Diabetes Glucose Activity Dataset

Patient Number	Age	Blood Glucose Level (mg/dL)	Physical Activity Level (steps/day)	BMI (kg/m^2)
1	45	150	8000	27.5
2	50	180	5000	30.2
3	38	140	10000	24.8
4	60	200	3000	32.1
5	55	160	7000	29.3
6	47	155	6000	28.4
7	53	190	4000	31
8	42	130	11000	25.6

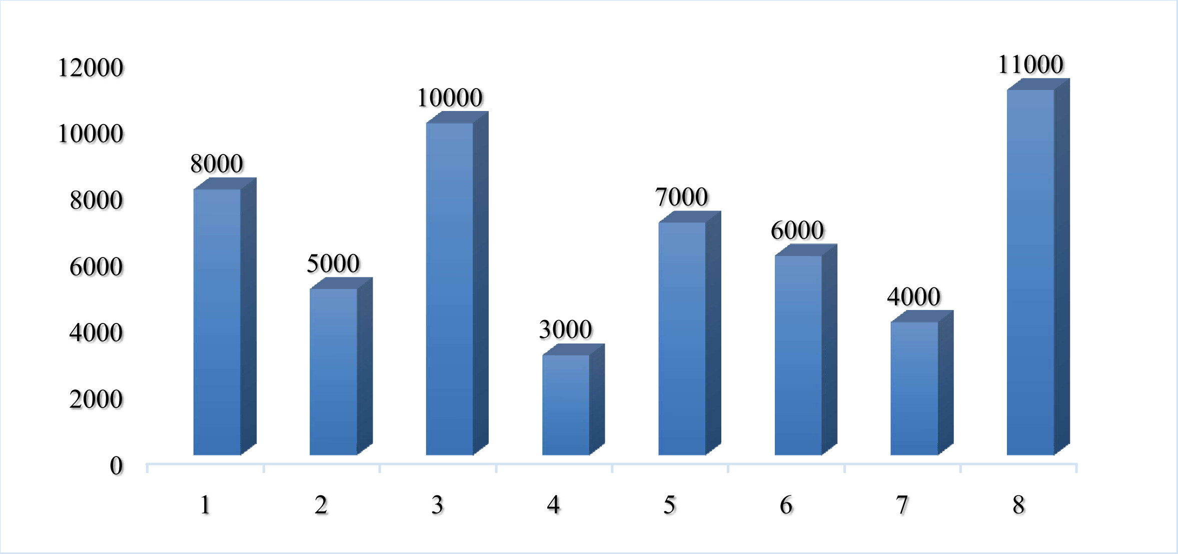

Figure 2: Physical Activity Level (steps/day)

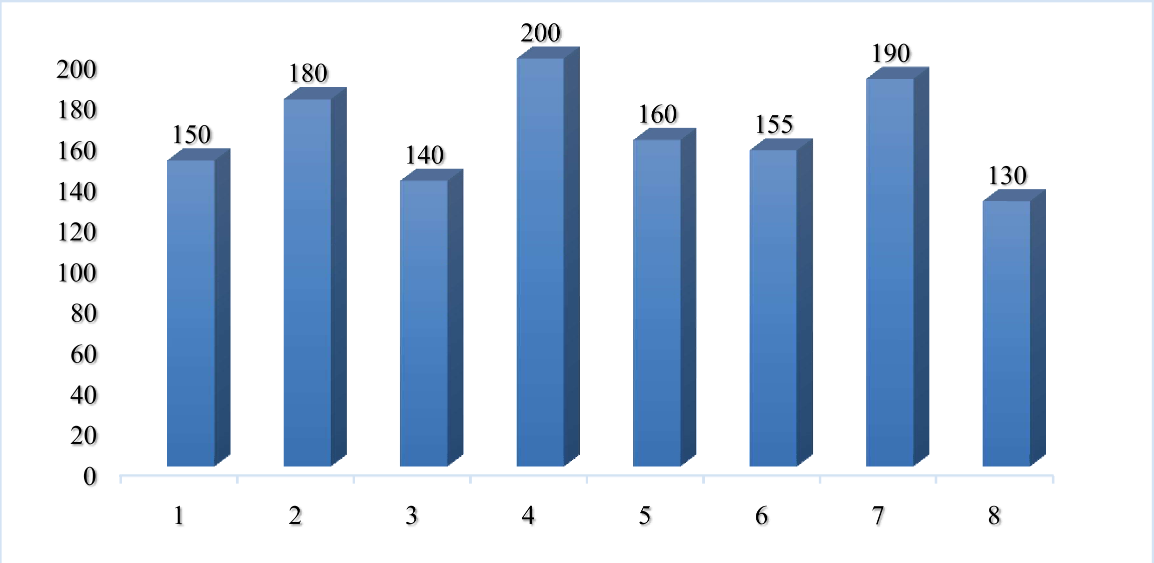

Figure 3: Blood Glucose Level (mg/dL)

Table 2 IoT Diabetes Glucose Activity Dataset; it is obtained along with the details of the patient's age, body mass index, blood glucose, and activity level. Blood glucose of the patients was highly fluctuated in the range of 130 mg/dL to 200 mg/dL with different glycaemic controls within the subjects. The ages of the patients range from 38 to 60 years. Steps taken daily reflect significantly wide variation in the level of physical activity as well, ranging from 3,000 to 11,000, indicating diverse levels of physical activity that possibly can be influencing blood glucose levels.

However, it has to be noted that patients with higher blood glucose levels, for example, Patient 4 who had highest blood glucose value 200 mg/dL accompanied by low level of activity of 3,000 steps, have generally been reported to have lower activity. The BMIs of the patients ranged from 24.8 kg/m² to 32.1 kg/m², with half of the patients at normal weight and the other half at excess weight.

Table 3: Correlation Analysis

	Age	Blood Glucose Level (mg/dL)	Physical Activity Level (steps/day)	BMI (kg/m²)
Age	1	0.55	-0.15	0.32
Blood Glucose Level (mg/dL)	0.55	1	-0.68	0.45
Physical Activity Level (steps/day)	-0.15	-0.68	1	-0.4
BMI (kg/m²)	0.32	0.45	-0.4	1

Table 3 Multicorrelation between Health Indicators showing Diabetes Management Ability Age, BMI, Blood Glucose Level, and Degree of Physical Activity A moderate positive correlation of 0.55 was seen between age and blood glucose level, which may indicate that elderly individuals have higher blood glucose levels. There are many other remarkable correlations associated with the correlation coefficients presented in table. There is a highly negative association in blood glucose level and level of physical activity, with a value of -0.68, which indicates that a more enhanced physical activity level implies having a lesser level of blood glucose. This thus highlights the role of exercise in the management of diabetes. Moreover, the relationship of moderate significance between blood glucose level and body mass index is 0.45, and they suggest that people with higher BMIs have usually higher blood glucose levels. The relation between BMI and age is 0.32, which can suggest that older people have a tendency toward higher BMI levels.

5. CONCLUSION AND FUTURE SCOPE

The implications of this research work clearly show how ML and DL may be leveraged to efficiently classify and analyze the collected health metrics generated from the IoT-enabled medical devices. Strong correlations were found between key health indicators in terms of data on cardiovascular and diabetes type, including heart rate variability, blood pressure, blood glucose levels, activity levels of the person, and BMI. The strong role that physical exercise has in the management of diabetes is underlined by the very strong positive association between age and blood glucose levels and by the negative relationship found between blood glucose and physical activity. Also, the role that body weight plays in the management of blood glucose is underlined by the fact that there is a moderately favourable relationship found between blood glucose and BMI. These outcomes recommend that IoT information should be merged with ML and DL algorithms to provide valuable, data-driven methods that improve administration of care for patients with long-term diseases. The strategy may thus lead to the accurate diagnosis, monitoring, and treatment planning of patients in the management of diabetes and cardiovascular disease. One of the future objectives of the study is to extend the possibilities of ML and DL application into real-time, pervasive analyses of IoT-enabled medical devices for broader and more diverse populations. Future research may include extending health measures to add additional and more personalized interventions to better manage chronic diseases and achieve better chronic disease outcomes; applying individualized, evidence-based recommendations for treatment; and using Internet of Things-derived data in electronic health records.

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