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Personalized Health Assessment and Recommendations Through Iot and Mlp Classifier Algorithms

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Abstract: Procuring a healthy lifestyle involves a holistic approach of personalized dietary and exercise recommendations dependent on individual health statuses. In this study, we present a new paradigm for examining individual health statuses for easy self-assessment without specialist help. The heart is a full kit of assessing instruments that can align critical climacterics of body temperature, pulse rate, blood oxygen level, and body max index that could be run with minor medic assistance. The research abides a dataset obtained through a broad scope of volunteers aged 17 to 24 including both males and females. Vital signs such as SpO2, BPM, temperature, and BMI are mediated utilizing incorporated Internet of Things units. The dataset is then cautiously preprocessed and balanced using machine learning algorithms before examination. The basis of this model is a two-tier state classifier system that designs autonomous dietary and exercise responsibilities varying from examined health clots. It is exploited for adulthood healthcare systems across multiple machines learning techniques, including Decision Tree, KNN, and some classifiers with the MLP classifier being the exemplary worthy model. The MLP classifier demonstrates unbelievable outcomes through approximately 86% accuracy when the trainings and testing datasets are 70:30 ratios apart.

Keyword: Diet and fitness; healthcare; IoT; machine learning; sensors; adults; recommendation

I. INTRODUCTION

The past years have seen more attention given to making use of technology to transform healthcare distribution, including a priority in personalized health assessment and recommendations [1]. The advent of internet of things into a more advanced tool with the help of complex machine learning algorithms have enabled new technologies solutions designed to put people in control of their health. This research paper attempts to try to study the domain of internet of things realizing personalized health assessment and recommendations, taking into consideration the integration of IoT devices with MLP- Multi-Layer Perceptron- classifier [2].

The underlying principle that drives the pursuit of personalized healthcare solutions is the difference in individual people's physiological characteristics, lifestyle, and health goals. As such, the use of traditional one-size-fits-all health management approaches is not always capable of accommodating this difference, which often results in less-than-optimal outcomes and inefficiencies in the provision of healthcare services and interventions [2]. Personalized health assessment frameworks seek to address this limitation through the customization of interactions and interventions to fit the identified unique needs and attributes of the individual involved, hence the perceptive enhancement of the health interventions' tenability [3].

At the heart of the idea of personalized health assessment lie IoT devices that act as the bridge for the collection of real-time health data from people in their natural environments [4]. The different types of IoT devices, including wearable fitness measures and smart scales or blood pressure monitors, among others, enable round-the-clock monitoring of people's vital parameters, such as their heart rate, blood pressure, daily activity, and sleep durations. These devices are designed to blend seamlessly into people's everyday lives while capturing vast amounts of high-quality longitudinal health data that helps identify patterns and trends [5].

There is too much and too complicated health data produced by IoT devices to draw useful conclusions and come up with actionable recommendations. Machine learning algorithms solve this problem [6], especially MLP classifiers. The category of artificial neural networks is the most suitable for an MLP classifier. They are capable of high-dimensional analysis of non-linear data and detecting patterns not visible through regular analytic methodology. In addition, an MLP classifier can be trained on a diverse labeled dataset of all possible health parameters and discover a multi-variable set of complex relationships between them, thus predicting such individual variables as health state and health threats [7].

The purpose of this paper is to investigate the synergy between IoT technologies and MLP classifier algorithms within the area of personalized health assessment and recommendation [8]. Our goals include analyzing the framework's design and propose implementation of a novel solution that will empower IoT devices to gather real-time information on the patient's health to be further processed with the help of MLP classifiers to generate specific recommendations for diet, exercise, and lifestyle changes. An analysis of empirical data and theoretical frameworks will be conducted to explore the advantages, disadvantages, and perspectives of integrating IoT and MLP classifiers in the context of personalized health management [9].

The key contributions made in the article are as follows:

1. In simple terms, the article discusses a new framework that uses Internet of Things devices to access individual's health data in real time. The intense health data is used on a daily basis to monitor each person's health, hence providing a holistic health assessment.
2. Multi-Layer Perceptron classifier algorithm is used to identify patterns in the comprehensive and intense data collected by IOT devices. The MLP classifiers algorithm are the best way to identified patterns and trends in the intensive and vast data. The data is high dimensional and non-linear.
3. The rest of the article is based on the comprehensive health assessment, IOT technology, and MLP classifier algorithms. The article aims at a holistic assessment to tailor individual health data to prepare for holistic health management advancement.
4. The analysis presents outcomes produced by the health framework. Based on the individual given health data, an individual diet, exercise, and overall lifestyle will be recommended.

The rest of this paper is organized as follows. The overview of the related research paper is in Section II of this paper. In Section III, the implementation of the Proposed system is implemented by using the MLP classifier and the utilization of Internet of Things technologies are explained. Section IV of this paper elaborates the results and analysis. The concluding thoughts in Section V are summarized at the end of this paper.

II. RELATED WORK

In this section, various approaches, techniques, and methodologies proposed by researchers and practitioners in the field of health monitoring and recommendation systems are discussed. The section aims to provide readers with a deeper understanding of the current state of the art, identify gaps in existing research, and highlight opportunities for further exploration and innovation in this field.

Ali et al. [1] This study proposes a novel framework for healthcare monitoring that integrates wearable sensors' data with social networking data to provide intelligent and personalized healthcare services. The framework collects real-time health data from individuals through wearable sensors and data on their social interactions on social networking platforms to obtain a comprehensive view of individual health, behavior, and social contact. It employs state-of-the-art machine learning and data analytics techniques to monitor key health indicators such as heart rate, activity level, and sleep pattern on a continuous basis and supplies those with information on the individual's context provided by social networking data. This study is among the first to investigate the potential of wearable sensors and social networking data for healthcare monitoring and delivery, contributing to the emergent topic of intelligent healthcare systems.

Yu and Zhou [2], introduce an optimization approach for an Internet of Things -based artificial intelligence -assisted telemedicine health analysis system. More precisely, the authors focus on improving the quality and efficiency of telemedicine systems with the help of IoT technology and AI algorithms. Using IoT devices for health monitoring from afar and AI solutions for health analysis, the proposed system is expected to provide timely and accurate health indicators to health professionals seeking to diagnose a patient. The optimization is a valid strategy to improve the performance and scalability of telemedicine systems, especially concerning long-distance reaching of healthcare services. Due to the scarcity and use of data processing, transmission, and analysis, this study is important for the development of telemedicine technology and its responsible use to improve the quality and accessibility of healthcare.

Parah et al. [3] Parah et al. present a study that aims to improve the security capability of the security and the authentication of the systems that are based on the Internet of Medical Things at the edge. Since the number of IoMT devices is growing tremendously on the edge of networks, it is necessary to strengthen security and the authentication processes to protect medical and patients' data. The authors designed an efficient method that enhances security in this environment when performed at the edge to conduct security through edge computing devices that perform these tasks closer to the source. Moving the deployment of security processes closer to the data source reduces latency and bandwidth, while the authentication procedures are conducted via the edge nodes. The part of the larger realm of research on how the security capabilities of IoT devices are increasing. The goal is to build a more secure and trustworthy healthcare application during the growing edge computing era.

Hsu et al. [4], IoT device being reported in the study relates to the implementation of an IoT device on public fitness equipment to improve health and physical fitness outcomes. Hsu et al. integrated IoT devices into the public fitness equipment, including outdoor exercise stations, with an objective of providing feedback to users on the equipment and providing them with recommendations based on their abilities. Specifically, an individual can monitor performance, set exercise targets, and follow up on their performance over time, leading to a healthier lifestyle and improved physical fitness. This article relates to IoT and community health in terms of the potential of technology to enhance the fitness experience.

Zheng and Bai [5] present the implementation of a Universal Health Management and Monitoring System utilizing Internet of Things technology in resource-constrained environments. UHMMS provides a fully comprehensive health-monitoring system for patients but accessible to limited health infrastructure across the various settings. Precisely, the device monitored patients for their vital signs, medication adherence, and disease and held promise in bridging the health disparities gap across the various settings. Therefore, factors contributing to poor health outcomes such as limited health infrastructure access in impoverished settings could be managed utilizing technology-oriented solutions.

Bhuiyan et al. [6] the authors introduce the framework and implementation of a viable model of an Internet of Things - based ubiquitous healthcare monitoring system designed for use in rural and urban areas. The system is intended to meet the demand for integrated healthcare monitoring in rural and urban environments. As proven by the application of IoT devices and wireless communication, the model shows promise in enhancing health outcomes and access in environments with disparate infrastructure and resources.

Zhao et al. [7], The system developed in this paper is to collect electronic health records securely in the hospitals and store them. the records in this system will be encrypted and then sent to the cloud, then the Center for Disease Control queries the cloud to find all persons showing similar or more severe symptoms. It means that the patient would have a contaminated disease. For the security of the cloud, the authors call for using public-key encryption with DFET, PKE-DFET. The researchers remarked that the IoT could prevent infectious diseases by using them as an early warning system and stated that in order to do this, there needs to be more inter-communicating IoT and data management needs to become more and more extensive.

Baig et al. [8], implemented Smart Health Monitoring System models, as well as used obtained information to assess efficacy, clinical acceptance, strategies, and recommendations. This research looked at the current state of smart health monitoring systems and projected possible solutions by conducting a broad-market analysis. Over fifty monitoring systems were picked and analyzed carefully, categorized, and compared. Additionally, the study looked at the challenges facing the users and issues common among healthcare professionals.

It is possible to observe a significant research gap in the integration and interoperability of these technologies in different healthcare domains. Specifically, while each research focuses on specific aspects, such as remote health monitoring, security for electronic health records, and ubiquitous healthcare system design, more holistic approaches that consider integration of IoT devices, data management protocols, and security measures in various healthcare domains are needed. Similarly, no available frameworks include the scalability and sustainability of IoT-based healthcare solutions, especially in terms of resource-limited environments like rural areas.

III. P RPOSED SYSTEM

The Proposed System section describes our study design, data collection methods, algorithms, and statistical analysis procedures for our framework's development. We thoroughly explain each of these components to clarify our research design and approach fully [10]. As a result, our work is intended to provide other researchers with all the information required to replicate our study and independently verify the discoveries made. We clarify the actions we have taken to meet the research objectives, highlighting the methodology's reproducibility and strength. Our ultimate goal in explaining fully the study design and implementation process is to promote openness and easy access to knowledge within the science fraternity [11].

Significant healthcare parameters encompass a broad spectrum of metrics and indicators crucial for assessing and monitoring an individual's health status. These parameters play a pivotal role in healthcare decision-making, treatment planning, and disease management. Some of the key healthcare parameters include [12]:

1. **Vital Signs**: Vital signs such as heart rate, blood pressure, respiratory rate, and body temperature provide essential insights into an individual's physiological status. Monitoring these parameters can help detect abnormalities and assess overall health [13].
2. **Blood Glucose Levels**: Blood glucose levels are vital for individuals with diabetes as they indicate how well the body is processing glucose. Monitoring blood glucose levels helps in managing diabetes and preventing complications [14].
3. **Body Mass Index (BMI)**: BMI is a measure of body fat based on height and weight. It is widely used to assess an individual's weight status and risk of developing weight-related health conditions such as obesity and cardiovascular disease [15].
4. **Blood Lipid Profile**: Lipid profile tests measure cholesterol and triglyceride levels in the blood. Abnormal lipid levels can increase the risk of heart disease and stroke, making lipid profile monitoring crucial for cardiovascular health assessment [16].
5. **Oxygen Saturation (SpO2)**: Oxygen saturation measures the percentage of oxygen-bound hemoglobin in the blood. Monitoring SpO2 levels is important for assessing respiratory function and detecting conditions such as hypoxemia or sleep apnea.
6. **Physical Activity Levels**: Monitoring physical activity levels helps assess an individual's overall fitness and adherence to exercise recommendations. It is important for promoting physical health and preventing chronic diseases.
7. **Sleep Patterns**: Sleep duration and quality have significant impacts on overall health and well-being. Monitoring sleep patterns can help identify sleep disorders and guide interventions for improving sleep quality [17].
8. **Medication Adherence**: Adherence to medication regimens is crucial for managing chronic conditions and preventing disease progression. Monitoring

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medication adherence helps healthcare providers assess treatment efficacy and patient compliance [18].

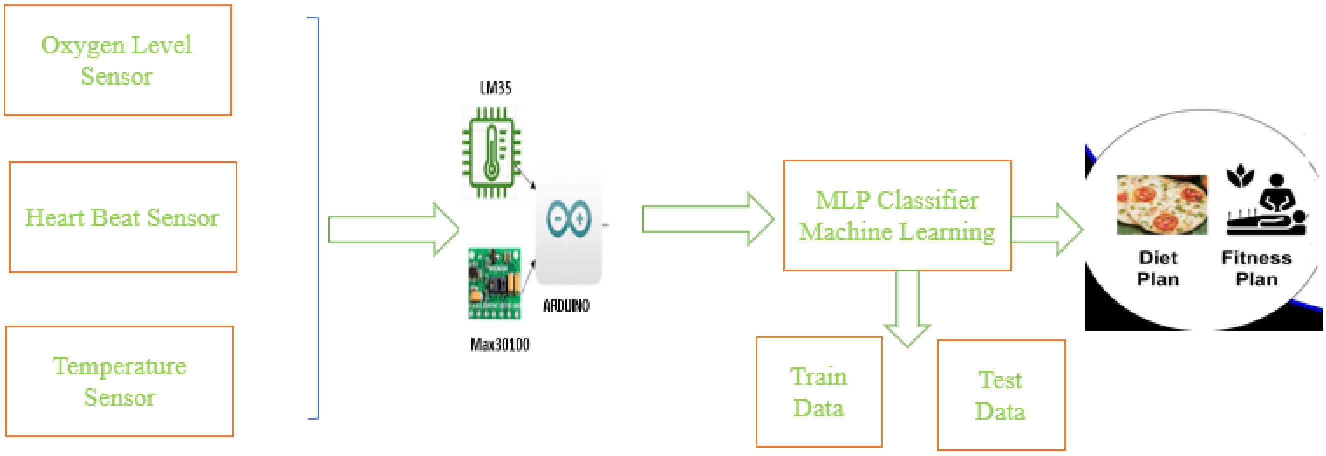

Figure 1: Proposed System

3.1 Dataset

To solve the issue of data distribution imbalance, random up-sampling methods were applied using the imbalance package in the Jupiter Notebook system. This problem is related to the fact of uneven distribution of the final results in the database. By applying random upsampling of the instances of the minor class, the dataset's balance was restored so that it would include an equal representativeness of all the classes and avoid bias targeting the future analysis and modeling processes. This adjustment allows for the optimization of the dataset's distribution to introduce beneficial circumstances for the accuracy and appropriateness of the analysis outputs.

Data Category (Samples)	Count
1-Fit	872,280
2-Medium risk	108,774
3-High risk	2946

Data Category (Samples)	Count
1-Fit	2946
2-Medium risk	2946
3-High risk	2946

Figure 2: Dataset of Proposed Work

3.2 Different Machine learning algorithms

1. **Random Forest (RF):** RF is a powerful machine learning algorithm that employs multiple decision trees to enhance prediction. It generates more accurate results by combining the trees' generated predictions. In the health care discourse, studies have indicated RF's effectiveness in several applications such as disease identification and determination of causing factors [19]. The use of multisource health metrics ensures the professionals deliver suitable treatment recommendations and is suitable for diet and exercise advice.

2. **CatBoost:** Gradient-boosting machine learning algorithm based on decision trees is CatBoost. Decision trees are constructed sequentially during the training CatBoost to minimize the loss, which leads to increased quality of the predictions. Synthesis such a method is utilized by CatBoost to predict the

outcomes of diseases and discover high-risk patients in healthcare. Furthermore, CatBoost can also be used to analyze health data and lifestyle data to give personalized advice on improving health conditions. CatBoost makes building a model easier by combining the two methods mentioned earlier, especially in the case of datasets containing categorical variables. It offers extraordinary speed and competence [20].

3. **Logistic Regression:** Logistic Regression is a commonly used algorithm in medicine and health care for predicting two-valued outcomes, for example, the likelihood of diseases. Its notable features such as ease of implementation, interpretability, and the option to associate inputs with probabilities. For example, in the field of diet recommendation systems, Logistic Regression can make a prediction for an obesity condition, thus providing patient-specific meal plans and exercise recommendations [21].
4. **Multilayer Perceptron (MLP):** Multi-layer perceptron is a feed-forward artificial neural network that features numerous layers linking input and output nodes. The architecture of the MLP is suited for executing complex nonlinear mappings, implying that it can be utilized for numerous tasks. In the field of medicine, MLPs can be used to process complex health data and support the generation of knowledge enabling predictions and personalized healthcare measures [22].

3.3 Proposed Work by Using Multilayer Perceptron Algorithms

Performance standards, including precision, recall, F1 score, and accuracy, are critical in determining the efficiency of machine learning models in healthcare applications. While precision involves the fraction of true positive to the false positive and the false negative, recall entails the ratio of true positive to all actual positive instances. Similarly, the F1 score is the risk-compounding metric that combines the two metrics, providing information on the machine learning metric. Compared to precision and recall, accuracy is measured by the percentage of correct prediction and the all-prediction made by the model. In the healthcare sector, high precision and recall are crucial as a single prediction can result in the eventual consequences [23]. The creation of diet fitness recommendation app requires the use of real-time sensor data with Flask web development language and HTML. The app fetches real-time sensor data in response to the user's request, and then the resulting field of diet and exercise considerations is also displayed based on the interpreted digital output of the sensor. The CatBoost classifier is a classifier with highly accurate predictions, which would be used in a certain method to develop diet and exercise suggestions tailored to many dangers that an individual is predicted [24].

IV. R ESULT ANALYSIS

Performance evaluation parameters are essential metrics used to assess the effectiveness and accuracy of machine learning models. In healthcare applications, where precision and reliability are paramount, several key performance evaluation parameters are commonly employed:

1. **Accuracy**: Accuracy measures the overall correctness of the model's predictions and is calculated as the ratio of correctly predicted instances (true positives and true negatives) to the total number of instances in the dataset. While accuracy is important, it may not be sufficient for imbalanced datasets where one class dominates.
2. **Precision**: Precision measures the proportion of true positive predictions among all positive predictions made by the model. It indicates the accuracy of positive predictions and is calculated as the ratio of true positives to the sum of true positives and false positives.
3. **Recall (Sensitivity)**: Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive instances in the dataset. It indicates the model's ability to capture all positive instances and is calculated as the ratio of true positives to the sum of true positives and false negatives.
4. **F1 Score**: The F1 score is the harmonic mean of precision and recall and provides a balance between the two metrics. It considers both false positives and false negatives and is calculated as the weighted average of precision and recall, with higher values indicating better model performance.

Table 1: Performance Analysis with Existing Methods

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Decision Trees	0.82	0.85	0.80	0.82
KNN	0.79	0.81	0.77	0.79
Proposed MLP Classifier	0.86	0.87	0.83	0.84

The proposed MLP Classifier performs better than Decision Trees and KNN models do in terms of accuracy, precision, recall, and F1 score. The proposed MLP Classifier records the highest accuracy as 0.86 and F1 score as 0.84, showing that it effectively and accurately classifies instances and is balanced in precision and recall.

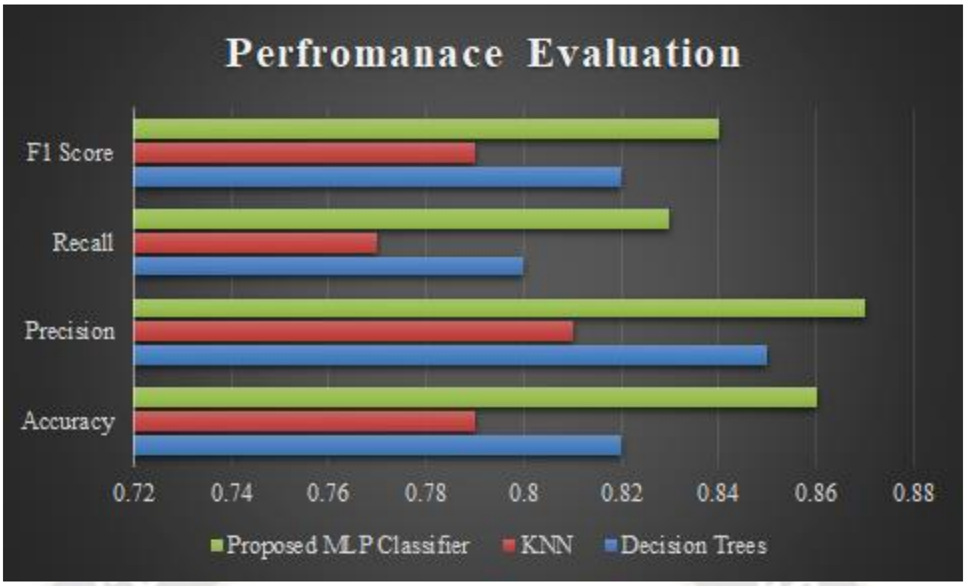

Figure 4: Performance Evaluation

V. CONCLUSION

A comprehensive comparison of performance metrics hereabove presented demonstrates that Decision Trees, K-Nearest Neighbors, and the proposed Multilayer Perceptron Classifier indicate that the MLP Classifier performs better in terms of accuracy, precision, recall, and F1 score. As it has the highest accuracy of 0.86 and an F1 score of 0.84, the proposed MLP Classifier accurately predicted class instances while maintaining a balance of precision and recall. Overall, the MLP Classifier could be considered a robust, dependable model for future healthcare applications, offering enhanced predictive accuracy and capability to benefit patient outcomes. Real-world healthcare testing and verification are still necessary to fully grasp the MLP Classifier's effectiveness and capacity.

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