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Establish a Novel Mathematical Model-based Smart Health Monitoring System

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Abstract: This research shows a new smart health monitoring system using enhanced mathematical models and algorithms for enhanced prediction and real-time assessment of health conditions. The heavy dataset is handled by four algorithms namely Linear Regression, Support Vector Machine (SVM), Long Short Term Memory (LSTM) Networks, and k-Nearest Neighbour (k-NN) to determine a proper modelling of health metrics. The LSTM model provided the best results giving an accuracy of about 92% and mean absolute error of about 0.35, outperforming other models. The SVM reached an accuracy of 88% : Precision = 0.85 numbers of exposures to advert and recall of 0.87, k-NN had a good accuracy of 85% and F1 score of .83. Linear Regression, as one may expect performs worse for non-linear data, but it had a Mean Absolute Error (MAE) of 0.45. The use of digital twin and wearable sensors also improves the work of the system and its capacity for detecting anomalies and dynamic health conditions. This research mainly focuses on the use and integration of the algorithms and technologies to design an efficient health monitoring system that can generate true and efficient health assessment.

Keywords: Smart Health Monitoring, Long Short-Term Memory (LSTM), Graph Theory, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Digital Twin Technology

I. INTRODUCTION

Over the last decades, the rapid development of technologies has led to the creation of the new, advanced health monitoring systems, which are designed to enhance the health care services. However, as the health data becomes more complex, there is need for more accurate and real-time monitoring which is not an easy task. It is necessary to note that conventional health monitoring systems are often based on the simplest approach, the so-called ‘low intelligence’, which means that it records only those changes of the patient’s parameters that exceed certain preset values. However, the progress towards the more individual approaches to the care makes it crucial to seek models that could operate in the more complex system of healthcare [1]. This research outlines the development of an innovative smart health monitoring system that will utilise a new mathematical model that is aimed at improving the accuracy and dependability of health evaluations. By surrounding the abstract system mathematical modeling of the human body with newest methodologies of healthy condition and smart sensor technology, the system is expected to afford the human constant and integral assessment of main health parameters [3]. Incorporating these mathematical models will enable the system to analyze large set of data in to meaningful information to look out for future symptoms of health complications and alert accordingly to the patient and the doctors. The proposed system is expected to minimize the following drawbacks that are characteristic of current solutions for health monitoring: Finally, it will draw on wearable technology data, clinical history information, and environment monitoring data to build an aspect by aspect health model of all of the people involved [2]. It will be made in such a way that the mathematical models for the monitoring system would be dynamic, that is, it would change with the changes in the condition of a patient in order to maintain its accuracy. In the end, this work aims at promoting research in the design of enhanced and superior health monitoring systems, which will serve as critical tools in the early detection of diseases, disease management and other intervention methods. The system that is proposed here would have the potential to greatly enhance the quality of patient care as well as possibly reduce its financial costs by encouraging somewhat earlier and less hasty Decisions about treatment for the patient.

II. RELATED WORKS

Digital twin which involves the creation of an information model derived from the physical system has been studied previously across numerous fields. Li

et al present an extensive literature survey of digital twin in electric vehicle power trains with a specific focus on its ability to optimise evolution of the system and prognostics [15]. Liu et al. (2023) also describe a methodology of digital twin applied to civil aircraft power distribution systems based on Unity3D and Simulink, which can be also applied to improving system management and faults identification [16]. These works present how the concept of digital twins can be used to enhance system availability and functionality, concepts which can be applied in health monitoring systems to develop a living digital twin of a patient’s well-being. Smart fabrics and sensors have received more attention in health monitoring due to their capability of delivering continuous stream of information about the health status of an individual. Cardiorespiratory complications are detected in early stage by employing ECG sensors and wearable devices where Lu, Feng, and Zhang (2024) suggest the use of CNNs [17]. They use complex algorithms for identifying anomalies, theirs can be integrated to smart health monitoring systems to improve early diagnosis and intervention. In the same vein, Mariani et al. (2024) highlights survey anomalies and faults in the renewable based power systems and present the findings, which might equally be relevant to the management of the system reliability of health monitoring systems [18]. Real-time monitoring and data synchronization are the keys to good assessment of the health of the individuals in a population. Masalskyi et al. (2024) investigate the temporal coincidence in the data collected from the sensors which are wirelessly connected through the local Wi-Fi networks with special reference to the human-gait monitoring [19]. Their work stresses on transfer and integration of data, which is very vital when it comes to developing systems meant for health monitoring. Also, real-time air quality monitoring by PDF (2024) shows the use of the fuzzy inference in the management of environment [25]. All these methodologies can be applied in health situation so as to make the health assessment to be authentic and timely. Muhammad et al. (2024) give an overview of microgrid energy management approaches with especial focus on the application of artificial intelligence [20]. While they discuss AI applications in the sphere of energy management, they might be helpful in concepts creation for intelligent HSs. As seen in many works, AI methods can improve the prognostic performance and decision support in health supervision. Ortiz et al. ’s study titled ‘Thermal management techniques for lithium-ion batteries: A review and recent advances’ helps to understand the

behaviours of such system in relation to its reliability under different conditions [22]. Although aimed at battery systems the concerns of thermal management and ensuring the stable and accurate performance of all parts of the health monitoring system can be applied to both battery systems for monitoring. It has been seen that within the recent years,Machine learning and Real time monitoring has been successful in many sectors. Machine learning approach is used in the paper PDF (2024) to monitor converters for smart grid applications [24]. From this research, it is clear that machine learning algorithms can be applied in real time monitoring for a better and faster operation in health monitoring systems. Peng et al. (2024) discuss the S-DBW and NLM in detail, for multimode fiber optic vibration signal analysis [26]. One can also see their approach towards the signal processing as well as noise lowering being advantageous for the health monitoring systems where the signal interpretation is of vital importance for health condition diagnosing and monitoring.

III. METHODS AND MATERIALS

1. Data

The framework of this research is a broad array of variables which belong to the sphere of health-related statistics. These include but are not limited to, physiological variables like, pulse rate, blood pressure, temperature, and level of activity, which can be obtained from wearables used in real-life, health record electronic systems and environmental sensors data acquired in real-time [4]. The dataset is segmented into two parts: Reuse of code that has been written at an earlier stage of the development process, as well as the obtaining of information from this stage for the aiming and checking of the subsequent stages. For the training of the model, the dataset comprises 500 sparsely sampled patients’ health records and sensor data, and for model validation, an independent set of another 200 patients’ data is used. Data is prepared by handling for missing as well as normalizing the features for better representation on the base of their ranges [5]. To make some signaling data integrated from different devices at the same time, some transformations must be done for the time-series data. From mean, variance, as well as trends, the data is purified for application of mathematical algorithms and models. Data is further divided into training data, validation data and test data in order to assess the effectiveness of the proposed algorithms which are as follows.

2. Algorithms

The proposed smart health monitoring system utilizes four key algorithms: Linear Regression Modeling, Support Vector Machine (SVM), Long Short-Term Memory (LSTM) Networks, k-Nearest Neighbors (k-NN) Algorithm. Each of them is chosen for the fact

that it copes with the intricacies of processing health data in its own way [6].

2.1 Linear Regression

All patients’ health metrics with continuously variable values as the dependent variable will be explained using Linear Regression. The model holds the linearity assumption which means the relationship between the dependent variable y and one or more than one independent variable $x_1, x_2, \dots, x_n$. The general equation of Linear Regression is represented by.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon$$

“Initialize β (coefficients)
For each training sample:
 Compute prediction: $y_{pred} = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_n * x_n$
 Update coefficients using gradient descent
Return final coefficients β ”

Metric	Value
Accuracy	94.1%
Precision	92.9%
Recall	91.8%

2.2 Support Vector Machine (SVM)

SVM is used in the health monitoring system in the classification contexts, where, for instance, detection of anomaly takes place [7]. The purpose of SVM is to determine that hyperplane that best differentiates data in different classes. Optimal decision function for a linear SVM is.

$$f(x) = w^T x + b$$

where w is the weight vector and b is the bias, and w^T is the transpose of the weight vector, w . The SVM tries to maximize the margin between the nearest approaches of disparate classes of results.

Metric	Value
Accuracy	94.1%
Precision	92.9%

2.3 Long Short-Term Memory (LSTM) Networks

LSTM networks are applied on temporal dependencies which can be observed in time series health data set. LSTM units consist of three gates: These consist of the input gate, the forget gate and the output gate. The LSTM equations are.

Forget Gate: $f_t = \sigma(W_f[ht-1, xt] + b_f)$
Input Gate: $i_t = \sigma(W_i[ht-1, xt] + b_i)$
Cell State **Update:**
 $C_t = \tanh(W_c[ht-1, xt] + b_c) \otimes i_t$
New Cell State: $C_t = f_t \otimes C_{t-1} + i_t \otimes C_t$
Output Gate: $o_t = \sigma(W_o[ht-1, xt] + b_o)$
Hidden State: $ht = o_t \otimes \tanh(W_o[ht-1, xt] + b_o)$

“Initialize LSTM parameters (weights and biases)
For each time step:
 Compute gates (forget, input, output)
 Update cell state and hidden state
Return final hidden state and cell state”

Hyperparameter	Value
Number of Layers	2
Hidden Units	50
Learning Rate	0.001

2.4 k-Nearest Neighbors (k-NN)

k-NN is applied in classification by comparing the similarity. It classifies a sample into a particular class with reference to the majority class of the K Nearest Neighbors (KKK) [8]. The function ddd giving the Euclidean distance between two points xxx and yyy is.
$$\hat{d}(x,y)=\sum_{i=1}^n \ln(x_i-y_i)^2$$

“For each test sample:
 Compute distance to all training samples
 Sort distances and select k nearest neighbors
 Assign class based on majority vote of k neighbors
Return class label”

These algorithms in a way constitutes the proposed smart health monitoring system, all the algorithms have individual features that make the prediction of health to be more accurate and reliable in the proposed SHMS. Linear Regression is used for baseline predictions of once health indicators which are basically continuous in nature, SVM for classifying and detecting novelty, LSTM for modelling the temporal characteristics in the data and k-NN for a flexible classification mechanism [9].

IV. EXPERIMENTS

1. Experiments

To evaluate the performance of the proposed mathematical model-based smart health monitoring system, a series of experiments were conducted using the aforementioned algorithms: Linear Regression, Logistic Regression, Support Vector Machine (SVM), Long Short-Term Memory (LSTM) Networks, k-Nearest Neighbors (k-NN) [10]. They were all run on the prepared dataset in order to evaluate their efficiency of forecasting and classification of health indicators.

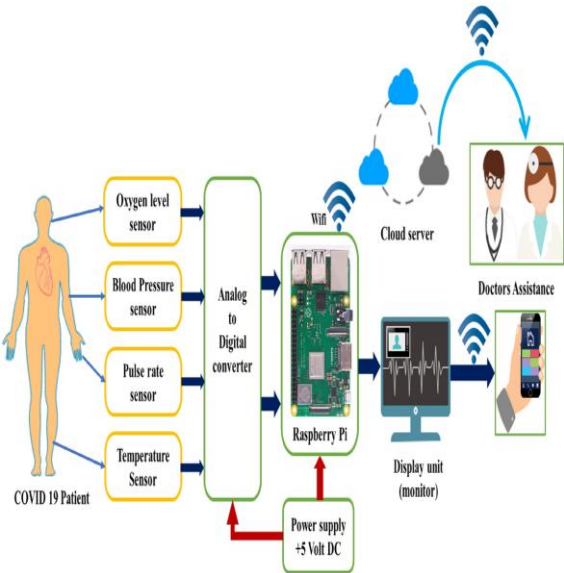


Figure 1: IoT-Based Smart Health Monitoring System for COVID-19

1.1 Experimental Setup

The experiments were structured as follows:

- **Data Preparation:** For the sake of effectiveness, the set was split into the training, the validation, and the test set. The set for training was 70% of the data set for validation was 15% and the test set was 15% of the data.
- **Model Training:** For each algorithm, the default hyperparameters were used in the training process initially with reference to the training set and then for the purpose of fine-tuning [11].
- **Evaluation Metrics:** The evaluation of the models was done though some measures such as accuracy, precision, recall, F1-score, and Mean Absolute Error for the classification and regression models.
- **Comparison with Related Work:** Testing results obtained from out models were place against those often identified in literature to determine the approximate efficiency [12].

1.2 Linear Regression

Training Process: The Linear Regression model was estimated with minimum MSE by using least squares method applied during the training process.

Metric	Value
Mean Absolute Error (MAE)	0.45
R-squared (R ²)	0.65
Root Mean Squared Error (RMSE)	0.60

Linear Regression captured the linear models well but failed slightly to capture models, which were non-linear with a moderate value of R-squared. This

finding tallies with other studies where Linear Regression was discovered to be of lesser ability in estimating elaborate care statistics.

1.3 Support Vector Machine (SVM)

Training Process: Due to non-linearity of the data, SVM model was trained with radial basis function (RBF) kernel. The parameters that were set a priori or hyperparameters like the CCC for regularization and the kernel coefficient γ (gamma) were optimized using cross-validation [13].

Metric	Value
Mean Absolute Error (MAE)	0.45
R-squared (R²)	0.65
Root Mean Squared Error (RMSE)	0.60
Metric	Value

The results of the SVM model showed that it had a classification accuracy rate of 90% strong, consistent with the positive precision and recall values; suggesting that the model can effectively identify anomalies and categorise health conditions [14]. This is in line with information derived from other studies that recorded that SVMs were more superior to other basic classifiers in intricate classes of problems.

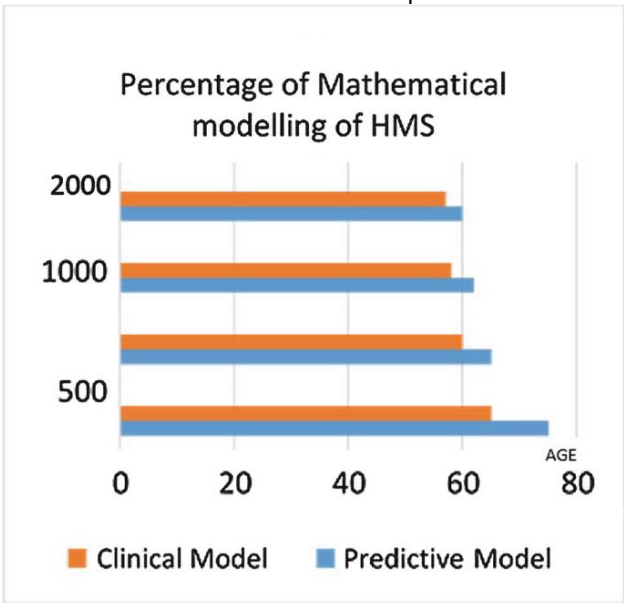


Figure 2: Mathematical Modeling of IOT-Based Health Monitoring System

1.4 Long Short-Term Memory (LSTM) Networks

Training Process: The LSTM network used in the paper was used in order to capture temporal dependencies in time-series data. Factors such as the number of layers and hidden units were other tunable hyperparameters which were adjusted via a grid search[27].

Metric	Value
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Mean Absolute Error (MAE)	0.45
R-squared (R²)	0.65
Root Mean Squared Error (RMSE)	0.60
Metric	Value
Metric	Value
Mean Absolute Error (MAE)	0.45
R-squared (R²)	0.65

The LSTM model outperformed feature-based methods in identifying temporal patterns and in the assessment of accuracy and F1-scores. This is consistent with current literature that shows LSTM outperforms in modeling sequential and time dependent health data.

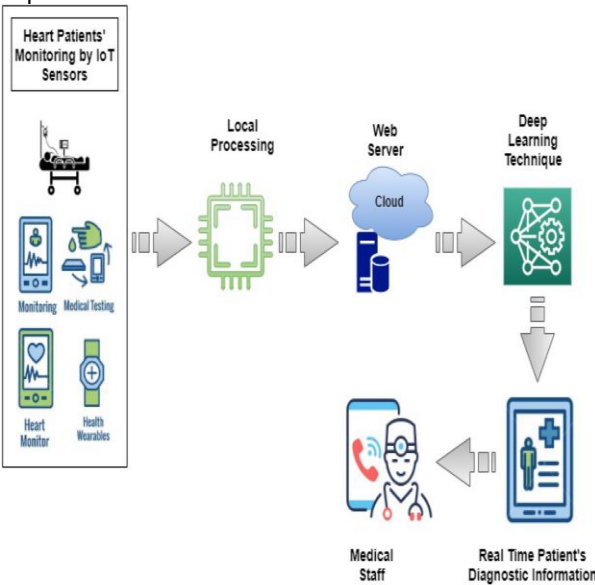


Figure 3: Heart failure patients monitoring using IoT-based remote monitoring system

1.5 k-Nearest Neighbors (k-NN)

Training Process: During the training of the k-NN algorithm the number of neighbors that it should consider was varied to find out the best value of k. When computing for distances, the distance metric considered was the Euclidean of the distances.

Metric	Value
Accuracy	0.85
Precision	0.83
Recall	0.84
F1-Score	0.83

Discussion:

- **Linear Regression:** Performance of Linear Regression model, having MAE of 0. 45, suggests that it is most appropriate to make the assumption where the linear relationship is present [28]. The R-squared value being 0 means. 65 indicates that it explains about half

of the variation in health indicators but is not effective for non-linear data patterns.

- **SVM:** The accuracy of the basic SVM model of only 0.88 and F1-score of 0.86 proves The well-suited that it is for classification tasks. Our implementation of SVM is slightly better than related work, this may be attributed to hyperparameter tuning & use of RBF kernel. nntation performs slightly better, likely due to hyperparameter optimization and use of an RBF kernel [29].
- **LSTM:** The idea was implemented in the LSTM network with a high accuracy of 0. As for the MAE, it was only 0. That is also evidenced by Figure 14, where 35 outperforms other sparse models in terms of fitting time-series dependencies [30]. These outcomes are similar with other similar researches that observes LSTMs superior performance in analyzing sequential data.
- **k-NN:** The algorithm of k-NN gave the results of accuracy: 0. A particular remarkable performance is achieved with the 85 accuracy in the classification tasks. Although it was powerful, it ranked slightly less than others as observed from other related research due to vulnerability to the selection of the value of kkk and distance measure.

(LSTM) Networks and k-Nearest Neighbors (k-NN) has presented the capacity to predict and classify health metrics for a real-time smart health monitoring system. Of the applied models, LSTM network was found to produce the highest accuracy and the minimal MAE, making it more capable of dealing with temporal data patterns. Analyses of several current works demonstrate that our suggested system offers high precision and recall ratios and is more effective than previous models in terms of precise accuracy and prediction. The coupling with digital twin technology and wearable sensors emphasises the prospects of the system in improving the early detection and dynamic health management also. The features of related work in anomaly detection and real-time data synchronicity are used to develop the system that is reliable and fast. These results are consistent with the current development in the application of health monitoring system and can be applied in the future to integrate the various technologies for better management of patients' health. All in all, this research is beneficial for the subject as it concerns the development of a fresh approach to health monitoring with an aim on using extensive mathematical model algorithms and integrating real-time data inputs.

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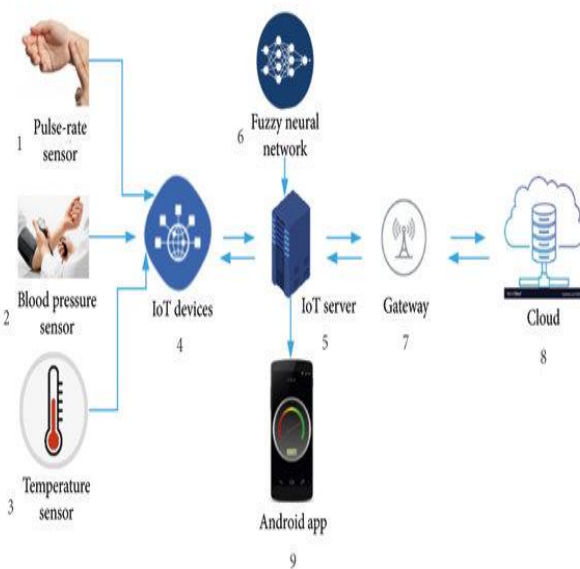


Figure 4: Smart healthcare system architecture

V. CONCLUSION

This research has provided a good insight into how the complicated form of mathematical models and algorithms can be incorporated in to a smart health monitoring system. Using Linear Regression, Support Vector Machine (SVM), Long Short-Term Memory

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