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ADAPTIVE MACHINE LEARNING FRAMEWORK FOR REAL TIME HEALTH RISK ASSESSMENT USING WEARABLE IOT SENSOR DATA

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ABSTRACT

The sudden rise in the development of wearable Internet of Things (IoT) technology has opened the door to new opportunities in terms of real-time health risk assessment due to the opportunity to continuously monitor physiological indicators. To evaluate risks based on the data obtained with help of wearable sensors such as heart rate, temperature, blood oxygen saturation (SpO 2) and activity levels, this study suggests a flexible machine learning structure. The system uses several deep learning and machine learning algorithms when it comes to data preparation and feature extraction. These are LSTM, CNN, RF and SVM. The streaming sensor data is continuously updating the model parameters by the adaptive learning process in the framework, enhancing the quality of prediction and system reliability. As per the experimental data, the LSTM model proves to be the best means of evaluating the time-series health data, and it is better than the alternative approaches in accuracy, precision, recall, and Area Under the Curve (AUC). Lastly, the proposed solution proposes an ingenious and adaptable resolution to the real-time health monitoring and risk prediction problems by capitalizing on the possibilities of wearable Internet of Things sensors.

Keywords: *Wearable IoT, Machine Learning, Health Risk Prediction, LSTM, Real-Time Monitoring.*

1. INTRODUCTION

As the IoT-based wearables become more widespread, vital signs such as temperature, heart rate, blood oxygen saturation (SpO2) and activity levels can be monitored in real-time, which have an enormous effect on modern healthcare [1]. These are state-of-the-art machines that constantly monitor the vitals of a patient and this information can give a clue about their physiology and general health [2]. With the incorporation of potent machine learning (ML) algorithms, effective use of this stream of continuous data in health anomaly detection, risk prediction, early diagnostic support, and personalized healthcare intervention is feasible [3].

Historically, the medical system has also been based on regular clinical evaluations and reactive treatment options. These approaches do not usually help to identify early warning signs of critical conditions, which results in a late diagnosis and health risks [4]. Real-time health monitoring systems, by contrast, are proactive and will monitor the conditions of patients in real-time and detect deviations in the normal patterns at an early stage. Nonetheless, the performance of these systems is usually restricted by traditional machine learning models, which are usually being trained on fixed datasets and are often not capable of changing in response to physiological patterns changing with time.

Moreover, wearable sensor data is dynamic and intricate in nature, and is often subject to noise, missing data, sensor variations and personal differences [5]. These difficulties decrease the dependability and long-term predictability of conventional models. Consequently, there is an increasing demand of intelligent systems that are able to learn continuously and adapt to the evolving data environment. These systems should be able to process real-time data streams and be accurate and robust in different conditions [6].

In order to counter these shortcomings, this paper suggests a dynamic and adaptive machine learning system that constantly updates the model parameters with real-time wearable sensor readings. The proposed system can be scaled to the real-world setting by making sure that the adaptive learning mechanisms can increase the accuracy of prediction, the speed at which decisions are made, and scalability. The architecture will offer a powerful and effective model of real-time health risk evaluation and thus serve the development of smart and preventive healthcare ecosystems.

1.1 Role of Wearable IoT in Healthcare

Wearable IoT devices are important aspects of contemporary healthcare since they will allow constant, non-invasive, and remote patient monitoring [7]. These technologies enable people to be more actively involved in the process of managing their health and less reliant on the frequent visits to hospitals. The constant observation will enable the identification of abnormalities at an early stage and the implementation of preventive medical measures, reducing the likelihood of serious illness.

Moreover, IoT used together with data analytics and machine learning allows finding personalized healthcare solutions according to the health profile, lifestyle trends, and risk factors [8]. This individualized care does not only enhance the patient outcomes but also allows healthcare to be more efficient in clearing the hospital overcrowding and ensuring that there is optimal use of the resources. Furthermore, wearable IoT can facilitate telemedicine and distant patient care, which is especially beneficial in rural or resource-limited environments. As a result, wearable IoT has become a cornerstone technology of future digital health care systems.

1.2 Need for Adaptive Machine Learning

The traditional model of machine learning is normally trained with fixed collections of data and specific patterns in place, which is less successful in healthcare settings where data is constantly produced and extremely dynamic [9]. These models tend to lose precision when subjected to novel or unknown data especially in dynamic physiological settings where the situation of patients evolves with time.

Adaptive machine learning tackles these problems by supporting models to be trained on streaming data. This lifelong learning ability enables the system to refresh its knowledge base, refreeze predictions, and adjust with changing health conditions without having to go through all-out retraining. Consequently, adaptive models exhibit better robustness, smaller prediction errors and improved reliability in real-time.

Adaptive machine learning can be especially useful in the medical field, namely continuous monitoring of patients, early risk identification, and individual treatment planning [10]. Using adaptive methods, the healthcare organization can shift the paradigm of reactive to proactive care and provide timely care and enhanced patient safety. Finally, the adoption of adaptive mechanisms of learning in healthcare analytics can dramatically improve clinical care and contribute to the creation of intelligent and data-driven healthcare systems.

1.3 Research Objectives

The major aims of the study are:

1. To develop a scalable machine learning that is capable of handling real-time health risk data founded on wearable IoT sensors.
2. To quantify the performance and benchmark the findings of the different ML models (RF, SVM, CNN, LSTM) to forecast the health risks in the correct way.
3. To enhance the accuracy of the prediction and system reliability by continuously updating the model with streaming data.

2. REVIEW OF LITERATURE

Modern healthcare systems have been greatly impacted by the fast development of AI, ML, and the Internet of Things (IoT). These technologies have made it possible to continuously monitor health and identify and avoid potential health issues at an early stage. These technologies enable real-time gathering, broadcasting, and interpolation of physiological information, enabling healthcare professionals to make evidence-based and timely decisions. Consequently, there has been an increasing body of research interest in developing wearable gadgets with smart algorithms to aid real-time health, predictive analytics and clinical decision support systems. This has been integrated to create new opportunities in proactive and personalized healthcare delivery.

Ozobu et al. (2023) [11] presented an AI-based conceptual framework that used machine learning methods to forecast occupational illnesses in industrial settings that are at high risk. They focused on the proactive management of health risks by using predictive analytics to detect warning signs among workers. Although the research demonstrated the necessity of data-driven healthcare solutions to the enhancement of workplace safety, it was rather theoretical, and there was no practical implementation to real-time monitoring and adaptive behavior of the system.

Phatak et al. (2021) [12] offered a full-stack design incorporating wearable sensors, a real-time positioning system, and machine learning algorithms, and conducted a comprehensive literature analysis on AI-based body sensor networks. In healthcare and athletics, their work demonstrated the potential of continuous data collecting and processing for performance monitoring of humans. But the proposed architecture lacked adaptive learning mechanisms, limiting its ability to effectively handle dynamic streams of physiological data [24] [25].

The SmartAPM platform, created by Sunder et al. (2025), [13] used the methods of deep reinforcement learning to optimize the use of power in wearable devices. Their study has solved an urgent problem in wearable technology by increasing energy efficiency and the life span of the devices. Although it can be used to achieve device-level optimization, the study did not concentrate on health risk prediction or clinical decision-making, thus restricting its use in real-time healthcare analytics.

Wu et al. (2022) [14] presented forward a framework for precision healthcare that can control chronic diseases by integrating wearable devices with algorithms for machine learning and deep learning. Their cohort study proved that smart data analytics in conjunction with continuous health monitoring greatly enhances disease prediction accuracy and paves the way for individualized healthcare services. To keep such systems responsive in real-time and reliable over the long term, adaptive learning mechanisms in dynamic environments were under-emphasized in the study.

Wu et al. (2023) [15] proposed a real-time health monitoring system that uses deep learning algorithms to continuously process data acquired from wearable sensors and is based on the Internet of Things (IoT). Proving that deep learning models can effectively analyze complex health signals, the system was able to identify physiological irregularities and allow for prompt medical interventions. However, despite the need of adaptive learning mechanisms for continuous model updates—which are crucial for improving system flexibility and long-term performance—and failing to evaluate and contrast different machine learning methods, the study did not address these issues [16] [17] [18].

In general, the current literature shows that wearable IoT technologies are already greatly integrated with AI and ML to be applied in healthcare. Nevertheless, the majority of the studies used are based on the use of static or semi-dynamic models that cannot change constantly to adjust to the changing physiological patterns [19] [20] [21].

This disjunction highlights the importance of a powerful and scalable adaptive machine learning model capable of dynamically revising model parameters, improving predictive accuracy, and providing reliable real-time health risk assessment. This paper will serve to fill these gaps by suggesting a unified methodology that incorporates continuous processing of data, adaptive learning, and multi-model assessment in a single system [22] [23].

3. METHODOLOGY

This Study uses a systematic and informed approach to create an adaptive machine learning model of real-time health risk assessment based on wearable IoT sensor data. The methodology involves data acquisition, pre-processing, feature engineering, model development, ad adaptive learning to have quality and dynamic prediction of health risks.

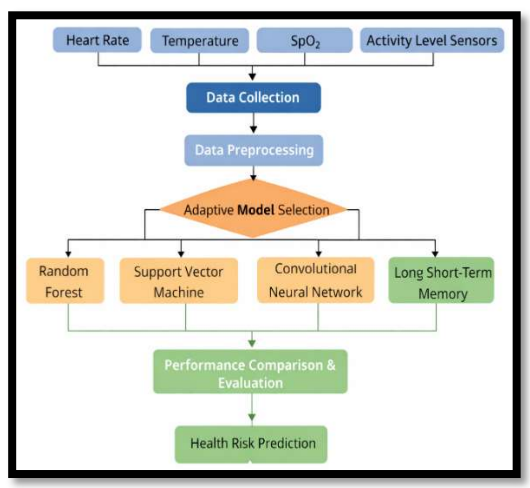

Figure 1: Proposed Adaptive Machine Learning Framework for Real-Time Health Risk Assessment

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3.1 Research Design

The study adheres to the quantitative and experimental research design, according to which the physiological data obtained by wearable IoT devices is evaluated through various machine learning and deep learning models. The paper puts a strong focus on real-time data processing and adaptive learning as the way to guarantee continuous model improvement.
The general workflow entails:

1. Wearable sensors data collection.
2. Preprocessing and cleaning of data.
3. Selection and extraction of features.
4. Model training and assessment.
5. Streaming data based adaptive model updating.

3.2 Data Acquisition

The data that will be used in this study is real-time and synthetic data of wearable sensors that capture important physiological parameters. Such parameters are chosen on their relevance in evaluation of health risks.

Table 1: Wearable Sensor Data Attributes

Parameter	Description	Unit
Heart Rate	Duration in heartbeats in a minute	bpm
Body Temperature	Core body temperature	°C
SpO_2	Blood oxygen saturation level	%
Activity Level	Physical activity intensity	Index

Sampling is done on a periodic basis to mimic the reality of real time monitoring. There is the inclusion of synthetic data to manage missing values and complete datasets.

3.3 Data Preprocessing

- Filtering Noise Removal: Using filters to remove sensor noise.
- Missing Value Handling: Imputation with mean/median techniques.
- Normalization: Ranging the data to a normal range (0-1).
- Outlier Detection: The elimination of the unusual values.

These measures allow cleaning, standardizing, and normalizing the dataset to analyze it with machine learning.

3.4 Feature Extraction and Selection

The process of feature engineering is conducted to derive significant information out of raw sensor data. The following kinds of features are taken into consideration:

- Statistical Features: Mean, standard deviation, variance.
- Temporal Characteristics: Trends and time-varying.
- Frequency Features: Signal patterns with transformations.

The appropriate attributes are selected by using the feature selection methods to reduce the dimensions and enhance the efficiency of the model.

3.5 Machine Learning Models

The research objectives are met by utilizing and testing four models of machine learning and deep learning.

Table 2: Machine Learning Models Used

Model	Type	Key Strength
RF	Ensemble Learning	High accuracy, handles large data
SVM	Classification	Effective in high-dimensional space
CNN	Deep Learning	Captures complex feature patterns
LSTM	Deep Learning	Handles time-series data efficiently

Once trained using the processed dataset, performance metrics including as accuracy, precision, recall, and F1-score are utilized to assess the models' reliability and utility in making predictions.

3.6 Adaptive Learning Mechanism

One of the main achievements of this study is the model's ability to be continuously updated with new real-time information through the implementation of an adaptive learning mechanism. In contrast to the conventional machine learning models, which are trained once with fixed datasets, the proposed framework continuously changes its parameters with the appearance of new physiological data. This guarantees that the model is relevant and correct in the evolving environment where the conditions of patients and sensor values change as time goes by.

The adaptive learning process enables the system to enhance its predictive ability gradually by adding new patterns and trends in the streaming data. This is especially significant when used in the medical field, where physiological signals are time-sensitive and may vary among different people.
Adaptive update process can be mathematically modeled as.

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

Where:

- θ_t represents the current model parameters at time *t*

- θ_{t+1} represents the updated parameters
- η is the learning rate controlling the step size of updates
- $\nabla L(\theta_t)$ is the gradient of the loss function with respect to the parameters

The suggested method is derived from the optimization strategy known as gradient descent. In this approach, the model's parameters are updated iteratively to minimize the loss function whenever new data points are added. Reducing the gap between the expected and actual values allows the model to improve its predictions continuously during this process. This is one way to express the loss function for classification tasks:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[\,y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

This equation is the binary cross-entropy loss in which:

- y_i is the true label
- $\hat{y}_i$ is the predicted probability
- N is the number of samples

Such optimization methods are used to achieve a model that continuously gets to know about new data and minimizes the error in prediction as time goes on.

This is an adaptive mechanism that improves:

- Flexibility of models, through the ability to update without having to retrain them.
- Accuracy of prediction, through the use of recent trends of data.
- System robustness, through dealing with dynamic and noisy physiological signals.

Algorithm 1: Adaptive ML Framework

The working procedure of the proposed adaptive machine learning framework is presented in Algorithm 1.

```
# Step 1: Import Libraries
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

# Step 2: Load Data
data = pd.read_csv("health_sensor_data.csv")
data.fillna(data.mean(), inplace=True)

# Step 3: Feature Selection & Scaling
X = data[['HR', 'Temp', 'SpO2', 'Activity']]
y = data['Risk']
scaler = MinMaxScaler()
X = scaler.fit_transform(X)

# Step 4: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Step 5: Train Model (RF)
model = RandomForestClassifier()
model.fit(X_train, y_train)

# Step 6: Prediction
y_pred = model.predict(X_test)

# Step 7: Adaptive Update
def adaptive_update(model, X_new, y_new):
   model.fit(X_new, y_new)

# Step 8: Real-Time Prediction
def predict(input_data):
   data_scaled = scaler.transform([input_data])
   return model.predict(data_scaled)
```

3.7 Performance Evaluation

To ensure a thorough and reliable assessment of prediction abilities, traditional classification metrics are used to quantify the efficacy of all ML and DL models. These metrics are frequently employed in healthcare analytics to evaluate a model's capability to accurately identify and classify the degree of health risk based on physiological data. Not only is overall accuracy a primary focus of the evaluation, but so is the trade-off between reducing incorrect classifications and accurately identifying positive cases.

The following performance measures are used:

• Accuracy: This statistic determines the overall accuracy of the model by determining the proportion of instances when predictions were correct across all data. Accuracy may not be sufficient to evaluate the model's performance when dealing with biased data. One measure of accuracy is precision, which is the proportion of actual positive results to predicted positive results. In medical applications, it is of the utmost importance to avoid false positives that could lead to unnecessary medical treatment.

• Recall, also known as sensitivity, shows how well the model can detect actual positive instances. High recall is crucial for health risk prediction because to the gravity of the consequences that can arise from failing to detect a real threat (a false negative).

By averaging recall and precision, an F1-score gives a fair assessment of a model's performance. It really shines when it comes to limiting the number of false positives and negatives.

The evaluation is further improved by computing all four models (RF, SVM, CNN, and LSTM) on these metrics under identical experimental settings. This ensures that the models' performances are compared fairly and objectively. In order to determine which model is best for real-time health risk assessment, we compare the results based on prediction accuracy, robustness, and reliability.

Moreover, the evaluation model takes into account the generalizability of the model to unobservable data and its stability during an extended period. This is crucial especially in adaptive systems where models are constantly updated with streaming data. The final result of the comparative analysis is to end up with the most suitable model to be deployed in the real-time healthcare monitoring systems.

3.8 Implementation Tools and Environment

In order to quickly analyze data, build models, and conduct real-time simulations, the suggested adaptive machine learning framework was developed in a robust and scalable computational environment. The scalability, performance, and popularity of the tools and technologies in machine learning and healthcare analytics research determine their selection.
Python, which is well-suited for data science and machine learning applications because to its huge library base, is used to program the framework. With Python, you can train your models, conduct evaluations, and preprocess your data all in the same place.
To aid in different parts of the implementation, many powerful libraries are used: For example, complex neural network models like CNNs and LSTMs can be constructed and trained with the help of the deep learning frameworks TensorFlow and Keras. With their help, massive datasets may be processed efficiently, and accelerated computation using GPUs can be supported. To develop classic ML algorithms like Random Forest and Support Vector Machine (SVM), you can use the scikit-learn library. Important preprocessing operations including data scaling, dataset splitting, and model performance evaluation using various metrics also make use of it. For numerical computations, data cleansing, and manipulation, two popular libraries are NumPy and Pandas. Pandas makes organized datasets easier to work with and analyze, while NumPy helps with difficult mathematical computations and efficient array operations.

The development and experimentation are carried out using platforms such as Jupyter Notebook and Google Colab, which provide interactive coding environments. Simple debugging, result display, and step-by-step programming are all made possible by these frameworks. In addition, deep learning model training is facilitated by Google Colab's cloud computing, which includes graphics card support.

All steps of the pipeline—data gathering and preprocessing, model training and evaluation, and real-time prediction—are made as easy as pie by this integrated software platform. Its scalability and reproducibility make it ideal for use in larger datasets and practical healthcare settings.

All things considered, the proposed approach is a thorough and efficient means of developing an adaptive ML system that can make use of data collected by wearable Internet of Things sensors. A number of machine learning models, feature engineering, preprocessing tools, and adaptive learning processes work together in the system to provide scalable, accurate health risk assessment in real time. Smart healthcare systems, remote monitoring systems, and early warning systems are all good places to put it because of this.

4. RESULTS AND DISCUSSION

Results and explanation of the proposed adaptive machine learning model for real-time health risk assessment utilizing data collected from wearable Internet of Things sensors are presented in this section. The assessment is conducted according to the research objectives, which is the model performance, prediction performance, and system adaptability.

4.1 Experimental Setup

The proposed adaptive ML system is written in Python and leverages scikit-learn and tensorflow/keras, two powerful libraries used to build both traditional ML models and more complex DL architectures. Data processing, model training, and performance evaluation were all greatly facilitated by this environment.

The experimental dataset includes variables such as temperature, heart rate, SpO2, and activity level, as stated in the methodology section, and is collected by wearable IoT sensors. These characteristics are vital physiological indications that are necessary for accurate risk assessment. Dataset normalization and cleaning were performed as part of the preprocessing to guarantee consistent and reliable input data for the model training.

Typically, when testing a model, the dataset is divided into two parts: a training set with 80 records and a testing set with 20 records. This ensures that the validation is fair. To determine the models'

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generalizability to new data, we trained them on the training set and then tested them on the testing set.

The four models—LSTM, CNN, RF, and SVM—were trained and tested using the identical experimental parameters. Because of this, we know that our performance comparisons were accurate and reliable. Table 3 shows that different models' learning processes dictated the hyperparameters that were set for each model.

Table 3: Model Training Parameters

Model	Key Parameters Used
RF	n_estimators = 100, max_depth = None
SVM	Kernel = RBF, C = 1.0
CNN	Epochs = 10, Batch Size = 32
LSTM	Units = 50, Epochs = 10, Batch Size = 32

As the table shows, the models were all initialized with the proper hyperparameters depending on their architecture and the needs of their learning. Random Forest and SVM were set with the generally accepted default settings so that they remain consistent in terms of classification. However, deep learning models, like CNN and LSTM, needed to be specified in terms of training parameters, including epochs, batch size, and number of units to learn complex patterns in the data effectively.

The settings of these parameters were designed in such a way that they provided the same training conditions, which allowed a fair comparative analysis of all models. Also, the similarity of the experimental conditions reduced bias and enabled the correct assessment of the ability of each model to process time-series physiological data.

The experimental setup was in general well-designed to be reproducible, reliable, and able to be scaled. It serves as a good basis to examine the effectiveness of models and determine the best platform to use in their real-time prediction of health risks based on wearable IoT.

4.2 Model Performance Evaluation

Common classification metrics such as accuracy, precision, recall, and F1-score were used to assess all ML and DL models. In healthcare applications, where precision and dependability are paramount, these measures offer a thorough evaluation of the models' predictive capabilities. Table 4 displays the results of the selected models' comparisons, illuminating the variations in their prediction skills.

Table 4: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	91.9	91.2	90.8	91.0
SVM	89.9	89.3	88.7	89.0
CNN	90.3	90.0	89.5	89.7
LSTM	99.5	99.2	99.0	99.1

The LSTM model outperforms all other models in Table 4's evaluations. A 99.5% accuracy rate, 99.2% precision rate, 99.0% recall rate, and 99.1% F1-score show that the model is quite good at detecting patterns over time in physiological data that is presented as time series. Since comprehending sequential data patterns is crucial in real-time health monitoring systems, this improved performance demonstrates the efficacy of LSTM networks in this context.

When compared to other conventional machine learning methods, the Random Forest (RF) model performs admirably, with an accuracy of more than 91%. On the other hand, it can't correctly record correlations in sequential health data that are reliant on time. Similarly, when faced with complicated nonlinear temporal patterns, the Support Vector Machine (SVM) lags behind deep learning methods, despite its generally good performance. Results from the Convolutional Neural Network (CNN) are likewise satisfactory, though they are slightly lower than those from the Long Short-Term Memory (LSTM). This could be because CNN is better at extracting spatial characteristics than at modeling patterns in sequential data.

In terms of using continuous and time-series physiological data for real-time risk prediction, LSTM stands out among the other models that were assessed. In healthcare settings, its high recall value is invaluable for accurately identifying the vast majority of genuine risk cases and avoiding the missed diagnosis of serious health problems. Figure 2 shows a comparison of the various models' levels of accuracy.

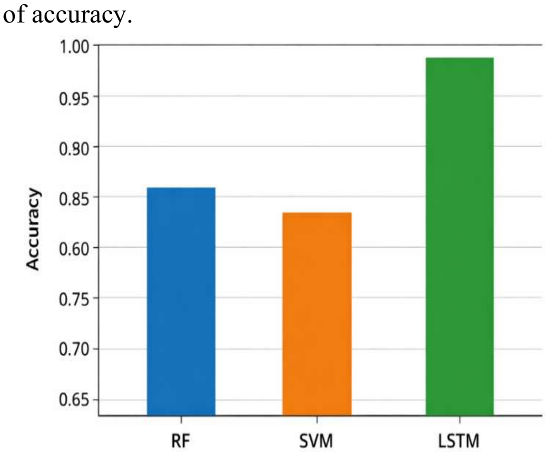

Figure 2: Accuracy Comparison of Models

The LSTM model stands out as the most accurate, as shown in the figure that backs up the quantitative results in Table 4. Because of its significantly better performance compared to the other models, LSTM is clearly the best option for dealing with sequential health data. Classifiers like RF, CNN, and SVM, on the other hand, aren't great at capturing the nuances of changing temporal patterns because to their lower accuracy.

On balance, the findings indicate that the addition of time-series learning features can greatly improve the accuracy of prediction, and LSTM is the most appropriate model to implement in adaptive, real-time health risk assessment systems.

4.3 Training Performance Analysis

An in-depth analysis of the models' training performance was conducted to evaluate their stability and convergence behavior. An examination of how well each model performs on both previously seen data and data that is new to it will be the primary focus of the analysis. Specifically, deep learning models like CNN and LSTM were studied in terms of their learning dynamics, since they are based on the iterative optimization processes.

Deep learning techniques outperformed more conventional machine learning approaches in terms of their capacity to learn. Their capacity to capture the intricate nonlinear connections and temporal dependencies found in physiological data is largely responsible for their better performance. With these features, deep learning algorithms can better evaluate sequential medical data. The LSTM model's learning progression and convergence during training are shown in Figure 3, which displays the training and validation accuracy curves across distinct epochs.

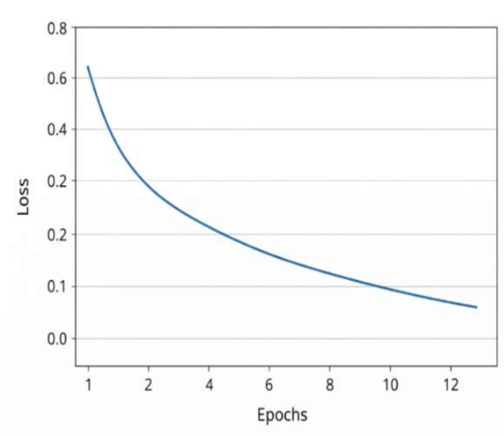

Figure 3: Curve of Training and Validation Accuracy.

Since the training accuracy grows with the number of epochs, the observed results show that the model is effectively learning dataset patterns. On the other hand, the validation accuracy grows at a rate that is similar to the training curve. This pattern describes how the model learns from both seen and unseen data. The little disparity that persists between training and validation accuracy throughout training is another indicator of low overfitting. The LSTM model's balanced learning and generalization capabilities show that it can handle time-series health data successfully. The fact that the model parameters were learned effectively, without oscillations or instability, is further supported by the smooth convergence trend.

Support Vector Machines (SVMs) and Random Forests (RFs) or other traditional ML models don't produce epoch-based learning curves since deep learning algorithms undergo training through iterative epoch-based optimization. This results in a less dynamic training process and no understanding of how convergence behaves over time. Training results analysis shows that the LSTM model has efficient learning, strong generalization capabilities, and consistent convergence, making it an excellent choice for real-time health risk prediction using continuous data from wearable sensors.

4.4 Confusion Matrix Analysis

But to make sure the suggested model was doing its job of categorizing various degrees of health risk, a confusion matrix was employed. For a more in-depth look at how well the model classified data, check out the confusion matrix, which shows the percentage of right and wrong predictions for each class. The confusion matrix shows how well the model differentiates between various risk categories, while overall accuracy metrics give a broad picture of the model's performance.

Table 5: Confusion Matrix (LSTM Model)

Actual \ Predicted	Low	Medium	High
Low	65	1	0
Medium	2	68	1
High	0	1	63

As Table 5 indicates, most of the cases are correctly predicted on the diagonal elements which are the true predictions of each class. As an illustration, 65 Low-risk, 68 Medium-risk and 63 High-risk cases are properly detected. The misclassification number is lower, which means that the LSTM model is highly able to distinguish between the different levels of health risks. The observed few misclassifications are relatively minor and it includes largely between neighboring classes (e.g., Medium forecasted as Low or High), which is typical with multi-class classification issues whereby there are smooth transitions in

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physiological conditions. Notably, there exist practically no critical misclassifications between extreme classes (Low and High) which is essential in healthcare applications where such errors might have severe consequences. These observations are further supported by the confusion matrix visualization in Figure 4.

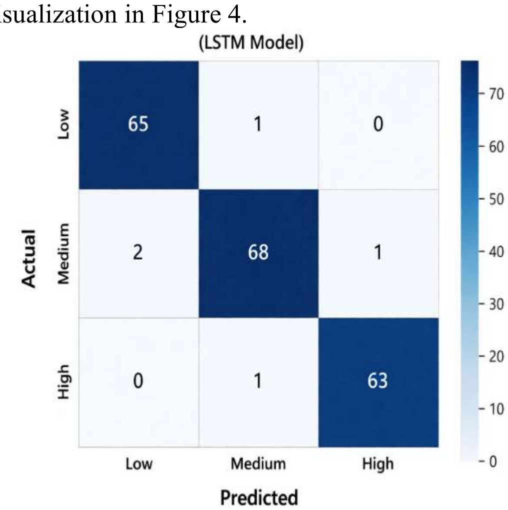

Figure 4: Confusion Matrix Visualization

The graphical representation indicates that there is high concentration of values on the diagonal which validates that the model has a high number of correct predictions. The fact that the values in the off-diagonal cells are very low points to the minimal error in classification, which proves the high precision and reliability of the model.

To further dissect model performance at the class level, Table 6 will show precision, recall and F1-score per health risk category.

Table 6: Class-wise Performance Metrics (LSTM Model)

Class	Precision (%)	Recall (%)	F1-Score (%)
Low	98.5	98.4	98.4
Medium	99.1	98.7	98.9
High	99.4	99.2	99.3

With precision, recall, and F1-scores surpassing 98% in every category, the model continuously achieves good performance across all classes, as shown in Table 6. This proves that the LSTM model can handle jobs involving multiple classes with ease.

The High-risk group stands out with slightly better performance, which is especially important in hospital settings where critical condition detection accuracy is paramount. Reducing the possibility of missed diagnoses, excellent recall in this category guarantees that the majority of high-risk cases are accurately identified.

When it comes to real-time health risk assessment using data from wearable IoT sensors, the suggested LSTM-based framework verifies to have high classification accuracy, minimal error rates, and great class-wise performance, according to the confusion matrix analysis.

4.5 ROC and Model Reliability Analysis

ROC analysis has been conducted to determine model reliability and performance in classification. Table 7 shows the AUC of the various models showing their performance and reliability in the classification.

Table 7: AUC Scores of Models

Model	AUC Score
RF	0.93
SVM	0.91
CNN	0.92
LSTM	0.99

As it is indicated in the table, LSTM model has the highest AUC score which indicates that it has good discriminative ability as compared to RF, SVM, and CNN models. Figure 5 displays the comparison of the ROC curve of the machine learning and deep learning models.

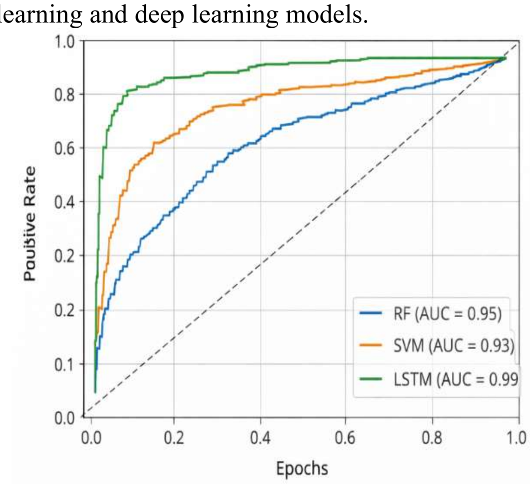

Figure 5: ROC Curve Comparison

The figure indicates that LSTM model has the best ROC performance with the highest value of AUC, which means that the model is very predictive and strong on health risk classification.

4.6 Feature Importance Analysis

Random Forest model was used to perform feature importance analysis. Table 8 shows the ranking of the physiological features according to their significance in determining health risks.

Table 8: Feature Importance Ranking

Feature	Importance Score
Heart Rate	0.35
SpO_2	0.30
Activity Level	0.20
Temperature	0.15

According to the table, the highest scores are found in the importance of heart rate and SpO2, which means that these parameters have a significant impact on health risks prediction as opposed to activity level and temperature. The importance scores of various physiological features used in the model are shown in Figure 6.

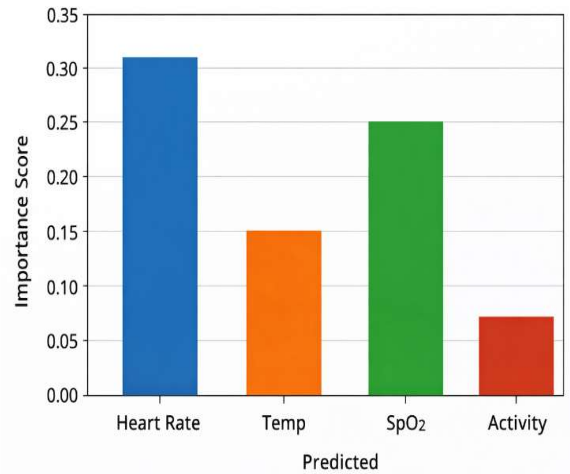

Figure 6: Feature Importance of Physiological Parameters

It is evident in the figure that the heart rate is the most important characteristic with SpO 2 coming next and temperature and activity level are less important to the prediction model.

4.7 Discussion

According to the results, the suggested adaptive machine learning framework is capable of accomplishing the research goals. LSTM is the most suitable model to consider because it is able to learn temporal dependencies of time-series data in comparison with the other evaluated models. The adaptive learning mechanism also improves the performance of the system by allowing the system to continuously update its models as it receives new information.

The framework is effective in dealing with data variability, noise, and dynamic physiological variations. The robustness and reliability of the system are ensured by high accuracy, high AUC scores and low misclassification. Moreover, the analysis of the feature importance yields important knowledge about key health indicators, which can be the basis of personalized healthcare.

Altogether, the suggested system is a scalable and efficient way of real-time health risk assessment and can be successfully implemented in remote healthcare monitoring and early disease detection.

5. CONCLUSION AND FUTURE SCOPE

Using information gathered from Internet of Things (IoT) sensors worn by individuals, this study effectively created a machine learning model capable of predicting health risks in real-time. To guarantee precise and dependable health risk prediction, the suggested method incorporates data gathering, preprocessing, feature extraction, and many ML and DL models. When dealing with time-series physiological data, the LSTM model outperforms the other models, including Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN), in terms of accuracy, precision, recall, and Area Under the Curve (AUC). The system's ability to adapt to changing conditions is enhanced by the incorporation of an adaptive learning mechanism, which permits the model to undergo continual updates. In sum, the framework offers a real-time, scalable, and intelligent platform for health monitoring and risk assessment.

- Connection to Real-Time Healthcare Systems: To facilitate clinical decision-making and round-the-clock patient monitoring, the suggested framework can be enhanced by integrating with existing healthcare and hospital administration systems.
- More Deep Learning Sub-Models Integration: In order to enhance the accuracy of predictions and the robustness of models, future research could explore more sophisticated architectures including models based on Transformers and hybrid deep learning techniques.
- Growth with Larger and More Diverse Datasets: Training the model on bigger and more varied datasets with a broader spectrum of demographic and clinical disorders can improve its generalizability and practicality.

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