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Classification of Healthcare Data Using Support Vector Machines with Stochastic Gradient Descent for Real-Time Wireless Sensor Network Monitoring

C. Seetha Lakshmi[1*], and Dr.A. Angel Cerli[2]

[1*]Research Scholar, Department of Computer Science and Information Technology, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai, Tamil Nadu, India.
ramesheethalakshmi@gmail.com, https://orcid.org/0009-0006-7068-0322

[2]Research Scholar, Department of Computer Science and Information Technology, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai, Tamil Nadu, India.
aangelcerli.scs@vistas.ac.in, https://orcid.org/0009-0002-1873-0848

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Abstract

The proliferation of wireless sensor networks (WSNs) in the health care sector has enabled continuous, real-time monitoring of patients' vital signs, enabling early diagnosis and prompt care. Still, the healthcare data classification techniques currently in use face critical challenges, including high computational cost and slow convergence, as well as limited scalability for large, real-time data streams. This research proposes the Optimized Healthcare Data Classification Model (OHD-Classifier) to streamline real-time monitoring systems by integrating Support Vector Machines (SVMs) with Stochastic Gradient Descent (SGD) (OHD-SVMSGD). As described, the OHD-Classifier advances SGD-trained SVMs, thereby accelerating convergence and improving efficiency. With this advancement, the OHD-Classifier improves classification accuracy for vital healthcare conditions, including irregular heart rates, critical- and low-variance hypertensive episodes, and other essential sign anomalies. The primary function of the model remains real-time data processing from WSNs, with provisions for instantaneous feedback to enable effective healthcare staff and decision-making. The solutions available today are hampered by slow model training due to the high dimensionality of the feature space, overfitting to WSNs, and unstable input data streams. The OHD-Classifier addresses the issues described through effective feature selection and the optimization of SVM parameters by SGD. This not only streamlines model training but also progresses the model's generalization to novel data. Outcomes indicate the OHD-Classifier outperforms all competing models on accuracy, training speed, and adaptability. The proposed model has the accuracy as 98%, Precision as 97%, Recall as 97% and F1 Score as 99%. This research lays the groundwork for developing more efficient, scalable monitoring systems in the healthcare sector and for improving patient care and outcomes in fast-changing, low-resource environments.

Keywords: Healthcare Data Classification, Wireless Sensor Networks, Support Vector Machine (SVM), Real-time Monitoring, Model Optimization. Feature Selection, Real-time Data Processing.

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*Corresponding author: Research Scholar, Department of Computer Science and Information Technology, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai, Tamil Nadu, India.

1 Introduction

Real-time patient monitoring systems are now made possible by Wireless Sensor Networks (WSNs). These systems tend to monitor the most critical signs: heart rate, blood pressure, and temperature. The extensive networks consist of numerous low-cost, lightweight sensors that monitor and collect large volumes of data. Support Vector Machines (SVMs), which are remarkably accurate classifiers, can handle high-dimensional data. (Álvarez-Alvarado et al., 2021) This characteristic applies to many healthcare functions, particularly illness prediction and modeling. However, static optimization of SVMs in highly variable, large-scale healthcare datasets will severely limit an SVM's usefulness and responsiveness. (Chander, 2022; Marhoon et al., 2025). This is where Stochastic Gradient Descent (SGD) is useful. As SVMs are used in real-time data streams from WSNs, SGD becomes increasingly important because it helps keep SVMs within a convergence threshold (Ismail et al., 2020). Instead of significant updates, which would move the SVM model from the healthcare sensor stream data, SGD makes frequent, minor updates during the training phase, stabilizing the model on noisy, highly variable datasets (Wu et al., 2023).

The combination of SVMs and SGD optimization approaches streamlines real-time classification, which is essential for continuous monitoring of SVMs. Enhanced SVMs, integrated with SGD optimization, streamline real-time classification, which is vital for constant monitoring. Enhanced SVMs with SGD optimization methods enable real-time classification, which is essential for continuous monitoring (Hu et al., 2020; Ma et al., 2020). The Enhanced SVMs with SGD streamline syndrome monitoring for real-time chronic illness and globally integrate chronic illness and responsive emergency healthcare. Rapid and accurate classification in real-time patient monitoring enables swift, individualized sensor-based intervention. Enhanced SVMs and SGD optimization approaches streamline real-time classification, which is essential for continuous monitoring (Abd Allah et al., 2022). The Enhanced SVMs with SGD streamline syndrome monitoring for real-time chronic illness and globally integrate chronic illness and responsive emergency healthcare. Rapid, real-time patient classification enhances swift, individualized sensor-based intervention. Enhanced SVMs and SGD optimization approaches streamline real-time classification, which is essential for continuous monitoring. Automatic prioritization of sensor data enabled swift, responsive intervention. Enhanced, rapid, and accurate classification of sensor data enables swift, individualized intervention. Streamlined real-time patient monitoring enables swift, individualized sensor-based intervention (Masengo Wa Umba et al., 2022; Giji Kiruba et al., 2023). Enhanced SVMs and SGD optimization approaches streamline real-time classification, which is essential for continuous monitoring. The Enhanced SVMs with SGD streamline syndrome monitoring for real-time chronic illness and globally integrate chronic illness and responsive emergency healthcare. Rapid, real-time patient classification enhances swift, individualized sensor-based intervention (Deepa et al., 2021; Heng et al., 2023).

In a given healthcare system, this wireless sensor networks are used to screen heart rate, blood pressure, body illness, and oxygen equal. Sensors for this monitoring method are useful across various settings, including chronic disease management and health monitoring (Junaid et al., 2022). Communication health emergency monitoring systems should also be developed with such networks. Such systems must undergo an elaborate process of classification, analysis, and decision-making. Support vector machines consist of concepts that lie near the hyperplane and are determined as the optimal level of the hyperplane. SVM is associated with achieving correct classifications (Liu et al., 2019; Mahmood, 2024; Verma & Kapoor, 2021). SGD is an optimization method commonly used to minimize the loss of machine learning models. When applied to SVM, SGD helps determine the best parameters and decision boundary to reduce the loss function, with key components including gradient Descent, stochasticity, and convergence (Sai et al., 2025). To integrate these notions into healthcare systems, such as chronic disease monitoring, elder care, and emergency care. The advantages of this proposed model include flexibility, low latency, and individualized health care (Massaoudi et al., 2021). The weaknesses of the current literature are sensitivity to hyperparameters and slow convergence; inability to solve concept drift; computational and memory limitations; class imbalance problems; sensitivity to noisy data; and scalability issues (Noshad et al., 2019). This paper incorporates hyperparameter tuning, adaptive learning rates, and incremental learning, of which some techniques are used for improving convergence, while others are employed for improving adaptivity. Several methods are employed to improve the computational efficiency of model compression and edge computing, along with mini-batch SGD, to address the issue of class imbalance through class weighting (Tran & Nguyen, 2008).

Key Contribution

- The integration (SVM) and (SGD) algorithms allows for the real-time analysis of healthcare data collected from Wireless Sensor Networks (WSN) which allows for timely intervention and continuous real-time updates on the necessary patient healthcare parameters needing ongoing treatment.
- SGD allows for the optimization of SVMs and the processing of estimated large-scale healthcare datasets allowing SVMs to be deployed in real-time which allows for the dynamic and immediate sensor datasets to be managed effectively.
- The model's scalability and adaptability to managing the growing amount of data available through the WSN was accomplished through incremental learning within a sliding window to address concept drift allowing the system to be responsive to healthcare data changes over periods of time.
- Incorporating SVM and SGD methodologies within a system enhances the model's robustness to noise which in turn improves the reliability and accuracy of classification rendering them usable in real-world conditions as intended.
- For systems intended for real-time healthcare monitoring, the sensitive healthcare data and metadata must be protected through active efficient privacy measures such as data encryption.

This document contains multiple sections, as elaborated upon below. ‘Section 1’ describes the research topic, the importance of the study, and the most relevant concepts. ‘Section II’ contains a literature review on the relevant topics and summarizes the past work done in relation to the study. ‘Section III’ describes the research design, including the proposed model within Support Vector Machine and stochastic gradient descent; its constituent parts and detailed algorithms, frameworks, and proposed algorithms; as well as an explanation of the interplay between Support Vector Machine and stochastic gradient descent. ‘Section IV’ contains the results and discussion, including a description of the dataset, an explanation of the assessment criteria, a comparative analysis of the results, and study performance with respect to the existing literature. Finally, ‘Section V’ concludes with an overall summary of the paper.

2 Literature Review

SVM and SGD are valued for their high effectiveness and seamless, real-time operation in intensive care and in classifying healthcare data within WSNs (Tirkey et al., 2020; Asefa et al., 2005). The use of WSNs in healthcare for monitoring patients' vital signs and real-time abnormality detection is an innovation that aligns well with remote patient monitoring, chronic disease management, emergency healthcare services, and other related fields. The ability to classify and predict healthcare situations from sensor data continuously is of utmost importance, for which a combination of SVM and SGD performs optimally (Liu et al., 2020).

SVMs are supervised learning models ideal for classification problems, especially in high-dimensional spaces, as is the case in healthcare data. Healthcare data usually includes sensor readings, such as heart rate, bp, temperature, and ECG signals (Hameed et al., 2025). These readings are incredibly dimensional and non-linear. SVM is most suitable for this job because it aims to find a hyperplane that best separates the data classes, minimizing classification errors (Abdullah et al., 2015). It is constructive in the medical field for distinguishing between healthy and pathological conditions and for diagnosing conditions such as heart disease or diabetes (Phongying & Hiriote, 2023). The extensive data produced from each nodes of a network needs categorization using SVMs for effective recognition of a health problem/anomaly, which recognize a health problem / anomaly, and for effective classification of a health problem/anomaly, and for effective classification of complex data sets while maintaining margins of errors: (Ayadi et al., 2017). SVM's lower tendency to overfit relative to other comparatives is of great importance, especially in medicine, where generalizing to new, unseen data is a crucial consideration (Chen et al., 2018). (SGD) is an optimization technique utilized in machine learning, and specifically in Support Vector Machines (SVMs), for minimizing certain functions. The efficiency with which SGD processes large amounts of data is an important requirement for (WSN), which generates huge volumes of sensor data in real-time (Hamzah & Othman, 2021; Zunaidi et al., 2018). In online learning, where new data is continuously available, SGD's ability to model continuously updates the learning drastically in sensor data streams (Janardhanan & Sabika, 2015). In healthcare, the need for faster real-time decision-making with less computational power is crucial since vital signs are monitored in critical, post-operative, and surgical units. The ability of SGD to train SVMs faster and with less computational resources has proven vital in time-sensitive situations (Khalaf et al., 2019). Given an SVM's capability for real-time classification and healthcare systems' preferences for such instant, precise classification, SGD perfectly suits these classification problems (Nayak et al., 2015). In real-time WSN systems, unvarying streams of sensor information are used to make sure the healthcare monitoring system rapidly filters the data stream (Tancev & Toro, 2021). Since the SGD algorithm updates model parameters sequentially, the system can pivot and dynamically continue learning. This feature proves advantageous when new, unobservable data streams into the system.

Research indicates the incorporation of SVM and SGD into real-time WSN systems produces favorable results. These models perform commendably on metrics of recall and F1 and accurately score streams of healthcare data of a temperature, and heart rate and blood pressure. For instance, one case noted an SVM trained with SGD achieving an accuracy of 96% for real-time data-stream analysis for detecting abnormal heart rhythms. The application of complex medical condition anomaly detection components record close scores in precision and recall along with high scores in accuracy, underscoring the importance of these components in the timely delivery of necessary medical care (Priyadarshi et al., 2025). In real-time SVM and SGD WSN systems, the need for personalization stems from the system's ability to respond to and dynamically adjust the patient's changing conditions. The need to employ SVM and SGD in WSNs for health data classification presents a myriad of problems. Perhaps the most severe problem with WSN health data classification is unbalanced data. This disproportionate data set places an additional burden on the detection of rare events as it is common in healthcare to encounter rare conditions. This problem can be alleviated by resampling, cost-sensitive learning, and specialized assessment measures such as Precision-Recall curves. Noise is also common in healthcare data due to sensor inaccuracies and environmental objects. Preprocessing, such as noise filtering, feature selection, and data normalization, is required to ensure the data used to train the models is more precise and reliable. This leaves ample room in the future to enhance the performance of SVM- and SGD-driven systems by incorporating other high-level methods, such as deep learning for feature extraction, and by hybridizing SVM with alternative algorithms, such as decision trees or k-nearest neighbors. It may become significantly easier to work with various forms of healthcare data and to address the issues with each approach (Sharrock & Kantas, 2023).

Research Gap

While using (SVMs) and (SGD) for real-time monitoring of a (WSN) shows promise, some gaps remain in the literature. These are the proper adjustment of imbalances in healthcare datasets, where typical medical events are often under-represented, and the optimization of models to operate on real-time data streams to handle continuously arriving sensor data without latency. Noise and error effects on the sensor data also require more complicated preprocessing techniques. It is also necessary to have individualized models that account for each patient's needs and simplify the expansion of extensive healthcare networks. Integrating information across numerous foundations, e.g., (EHRs) or imaging data, is another field that can enhance model accuracy. The fact that the SVM-SGD models can be explained is significant to clinical trust and decision-making. Finally, another evaluation methodology unique to medical applications should be considered in greater detail to ensure the models are applicable in practice. Solving these issues would make these technologies much more helpful, reliable, and popular in medical facilities

3 Research Methodology

3.1 Overall Architecture Diagram for Proposed Model (Ohd-Svmsgd)

The above (Figure 1) indicates a complete roadmap towards utilizing SVM (SVM) and SGD (SGD) in optimizing the classification of healthcare information in real time in a (WSN). In the initial processing stage, the data collection process starts, followed by real-time health information covered by various measures such as vital signs, heart rate, and blood pressure. These are all connected to the central hub or gateway. This live data is subsequently subjected to a series of procedures to ensure it is of high quality and fit for analysis. Removing irrelevant data and noise, down sampling to discard unnecessary records, and normalization and scaling to ensure features are comparable in a range are all elements of preprocessing. Appropriate feature selection guarantees that only the most salient data for classification are utilized. It maximizes the model’s usefulness and accuracy. Following data cleaning, the SVM classifier applies SGD for the classification of data into health normal and abnormal. Optimizations focus on the model parameters and improve learning speed, which is a critical advantage when working with real time large datasets. The design of the system is centered on achieving low latency which allows for timely classification that is critical for real time monitoring of healthcare data. Post classification of data, the system determines the vital signs and whether these are within the normal range. Any abnormality is forwarded to the SVM system, email, and/or dashboard which outranks the rest in the altered health status parameters. When deviations are detected, alerts of the changed parameters are instant. This enables the clinician to take action within the real time patient integrated health system along with a Decision Support System (DSS) that ensures constant monitoring of the patient. The configuration allows SVM coupled with SGD to streamline system monitoring, enabling advanced real time supervision of patients with critical and acute primordial health conditions. This improvement directly influences the quality of care provided and the health outcomes for the patients.

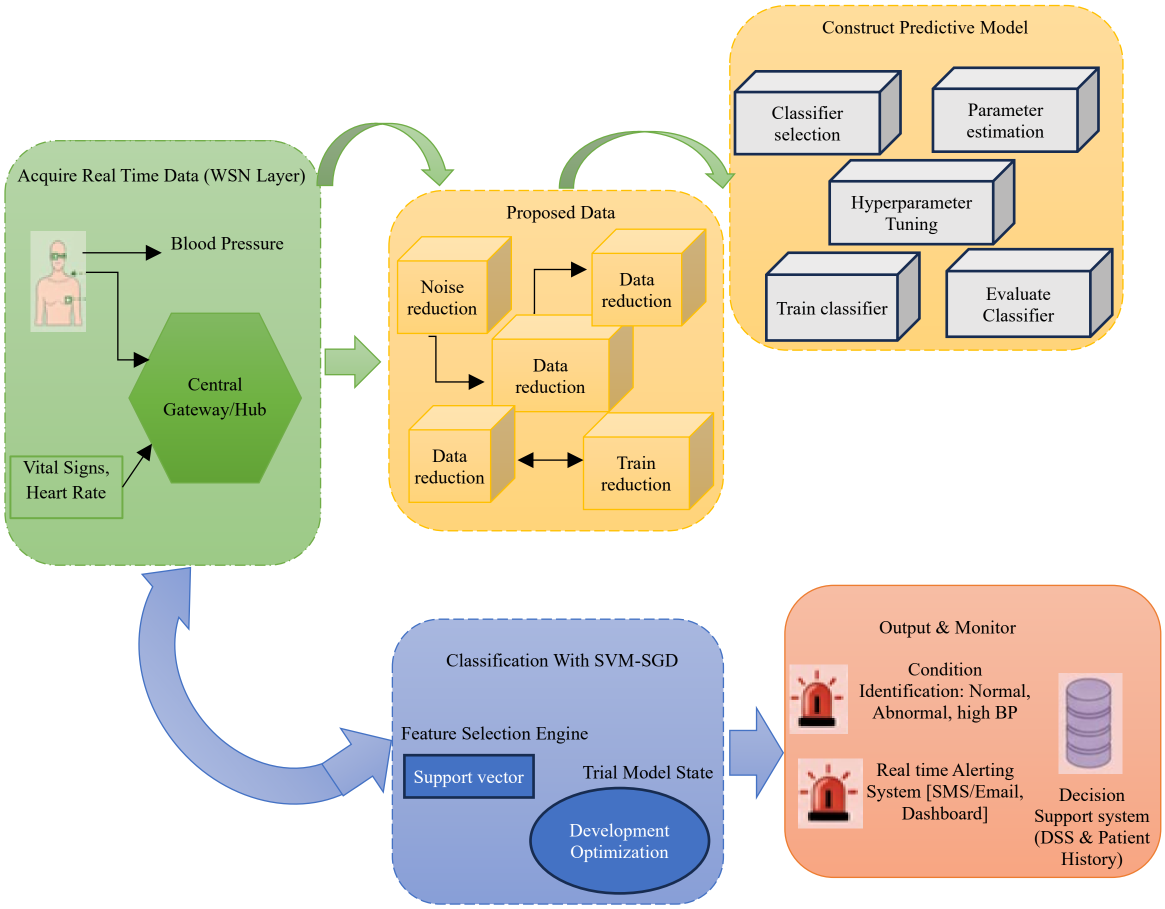


Figure 1: Overall architecture diagram of proposed model

3.2 Working Procedure of The Support Vector Machine for Real-Time Monitoring

Machine learning (ML) is the procedure of knowledge from experience and converting that experience into expectations. It's the concise explanation among the computer-generated programs to learn from the experience recorded over time. The main aim of this research is to assess the program's performance to improve the experience. Other than that, ML models interpret patterns learned from data collected during training to predict future behavior. Theoretical concepts of the SVM model are used to lessen the mechanical risk, which should be related to observed risk analysis, the training procedure, and the confidence range among the various dimensions.

Figure 2 illustrates how Support Vector Machine (SVM) classification works, focusing on the optimization and prediction steps. At first, the input features (x_1, x_2, ..., x_n) are shown as vectors, with each vector showing the features of a data point. Connected to support vectors, these vectors are crucial for determining the optimal hyperplane to partition the feature space into different classes. Support Vector Machine (SVM) methods construct linear hyperplanes to capture the range of the input dataset values. These functions assess the distance of higher-dimensional vectors and their geometric configurations. Within the optimization algorithm, parameters such as the kernel function and corresponding Lagrange multipliers (α_1, α_2, …, α_n) are configured to maximize the separation of the higher-dimensional classifications, thereby increasing the ease of the classification problem. After determining the Support Vectors and their parameters, the SVM moves to the prediction stage using the function of the predicted variable, $f(x)=\omega\cdot\phi(x)+b$, where ω is the weight vector, φ(x) is the mapping function of the features, and b is the bias term. The predicted output, which is used to classify new observations, is a linear mixture of the weighted support vectors. The graphic displays the components of the SVM model: support vectors, kernel functions, and optimization parameters. Each element contributes to improving the classification process's outcomes.

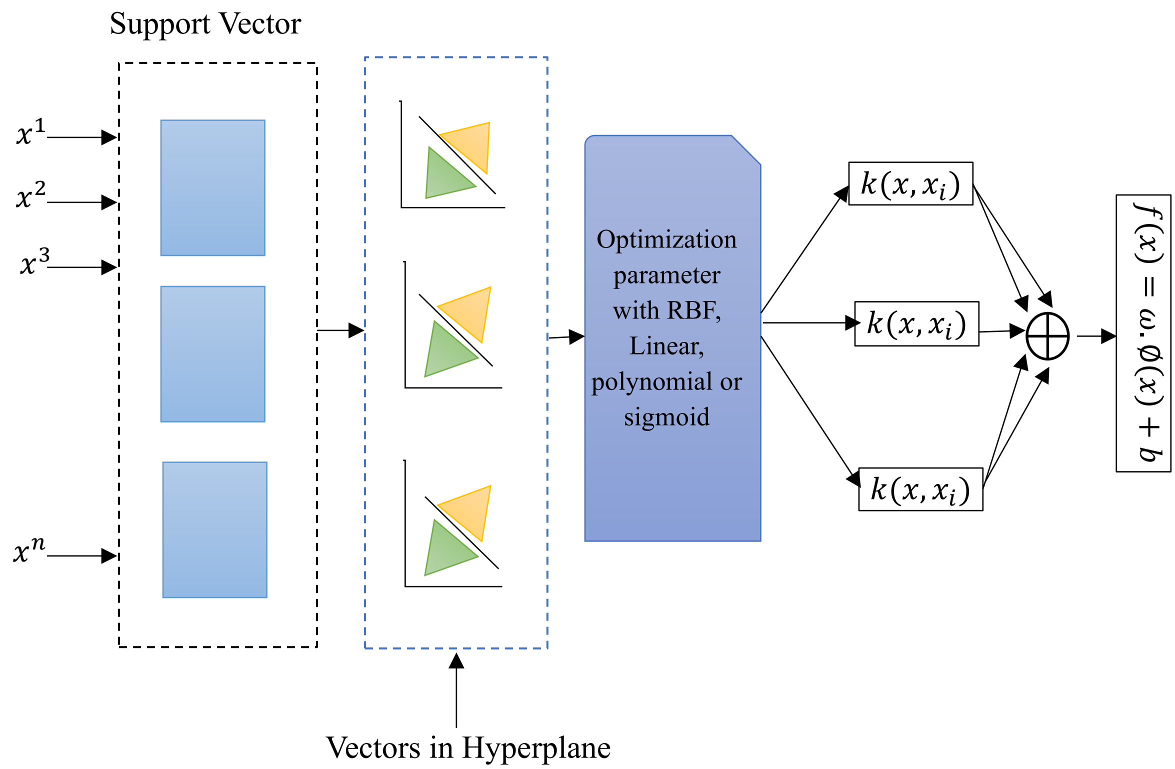


Figure 2: Working principle of support vector machine for real-time monitoring

3.2.1 Kernel Functions in SVM

SVM also describes a linear process that predicts data using available data. Essential elements should encompass the linear categorization within the transformed area. A specific mathematical tool called the kernel function is necessary for performing classifications; it helps in creating complex decision surfaces by transforming input data into higher-dimensional spaces where linear separation becomes possible through multiple parallel planes known as hyperplanes. Parameters within the kernel framework address the task of classifying data as discussed later on. In this context, the primary kernels employed include linear, polynomial, and radial basis function (RBF) types.

RBF, which is the function that should perform the non-linear mapping through samples that contain the higher-dimensional feature space, is noted as

$$K(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2\sigma}{2}\right) \tag{1}$$

From the above Equation (1) σ describes the kernel weight x_i and x_j They are noted as input followed by the ith and jth dimensions.

Linear Kernel Function, which is obtained by the SVM parameter described as

$$K(x_i, x_j) = x_i . x_j \tag{2}$$

Equation (2) mentioned the x_i and x_j Do the various dimensions follow inputs,

Polynomial Kernel function, it's a good example for a global kernel, followed by

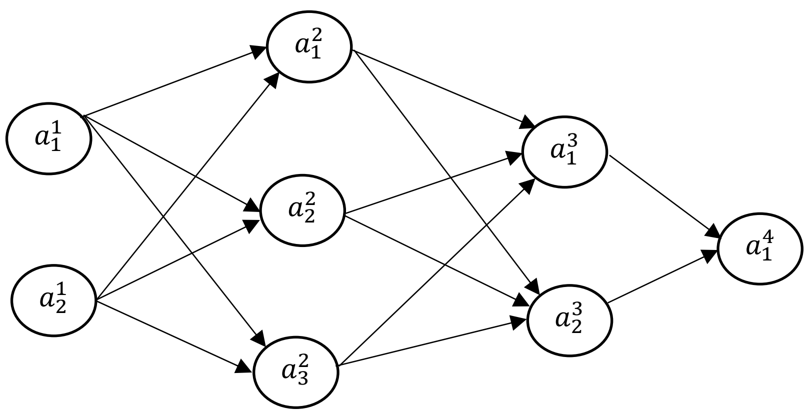
$$K(x_{i,}x_j) = \tanh(v(x.x_i) + c) \tag{3}$$

From the above Equation (3), v and c are adjustable kernel functions based on the data.

3.3 Working Procedure of Stochastic Gradient Descent for Real-Time Monitoring

3.3.1 Gradient Descent

Locating the local minimum of a differentiable function is the usual goal of this optimization approach. This is frequently used to optimize parameters before moving on to machine learning. The majority of optimization challenges in machine learning are focused on minimizing cost functions. These types of functions are known as objective functions. To update the various parameters in the opposite direction of the gradient used to reduce the target function's value when it approaches local minima.



Input Layer ϵR^2 hidden Layer ϵR^3 Hidden Layer ϵR^2 Output Layer ϵR^1

Figure 3: Working principle of stochastic gradient descent

Figure 3 shows a neural network with three layers Input, Hidden, and Output that illustrates the architecture of a multi-layer network. The input layer consists of two neurons (denoted as $a_1^1$and a_2^1) which belong to the space $\mathbb{R}^2$. These neurons receive input data and pass it to the next layer, the first hidden layer, which contains three neurons (a_1^2, a_2^2, and a_3^2) in the space $\mathbb{R}^3$. In the concealed layers, the hidden neurons carry out the computation of the input via the use of weights and activation functions, thus engaging in feature extraction. The output from the first hidden layer is passed on to the second hidden layer, which contains two neurons. At the end, there is an output layer in which a single neuron executes the ultimate prediction/classification. The neurons of the hidden layers create inter-layer communication and are connected by weights, which allows the network to recognize and learn intricate relational patterns in the data. The structure described exemplifies a standard feedforward neural network since there is a sequential flow of information from the input to the output, with each layer performing a different transformation of the data.

The objective function in machine learning decomposes the expectation over the pre-sample loss function for the training samples.

$$L(x, y, \theta) = \frac{1}{M}\sum_{i=1}^{M} L(x^i, y^i, \theta) \tag{4}$$

From the above Equation (4), L is noted as the loss function expressed as $\{(x^1, y^1), (x^2, y^2) .., (x^m, y^m)\}$ is also noted as training data, θ Also represents the training parameters, L is the pre-sample of loss, and M is the size of the training data.

To minimize such types of objective functions with gradient descent requires computing as,

$$g = \frac{1}{M}\sum_{i=1}^{M} \nabla_{\theta l}\left(x^i, y^i, \theta\right) \tag{5}$$

The average gradient of the total loss and ∇_θl is given by Equation (5), where g is the initial value. Individual samples were noted. The computing cost of Equation (5) is sometimes known as O(M). It will take a long time to practice on an extensive training set, according to the projections. The Stochastic gradient descent algorithm is used to lower computational costs. In SGD, the predicted loss is the central concept, and the entire training process, including L(x, y, θ), follows. Another aspect to consider is that these approaches, also known as mini-batch stochastic methods, often employ a training set. It is a common approach to simplifying stochastic processes. From activations and mistakes, one can derive the gradient using several equations. To find the cost function's gradient, one can use backpropagation.

3.3.2 Stochastic Gradient Descent Algorithm

$"Input: learning\ rate, \eta, epoch, T, initial\ parameters, \theta"$

$f, loss\ function, L, training\ set, \{(x^1, y^1), (x^2, y^2) \ldots \ldots .., (x^m, y^m)\}$

$for\ t = 1\ to\ T\ do$

$sample\ m\ from\ training\ set\ as\ a\ mini - batch;$

$Estimate\ expectation\ L(x, y, \theta_t) = \frac{1}{m}\sum_{i=1}^{m} l(x^i, y^i, \theta_t);$

$Estimate\ gradient: g = \nabla_g l(x, y, \theta_t);$

$Parameter\ update\ \theta_{t+1} = \theta_t - \eta g;$

$end;$

3.4 Data Flow for Algorithmic Framework

Figure 4 illustrates the workflow for real-time healthcare data processing using SVM with SGD for classification, monitoring, and prediction. To start with, the process is based on real-time data acquisition via WSN, which is also connected to various gateways via the raw data. To collect these types of data, it should be passed through preprocessing phases that handle missing values, scale the data, and extract features. After preprocessing, the data is classified using an optimized SVM-SGD model, where SGD is used for parameter tuning, and the model is updated iteratively to improve performance.

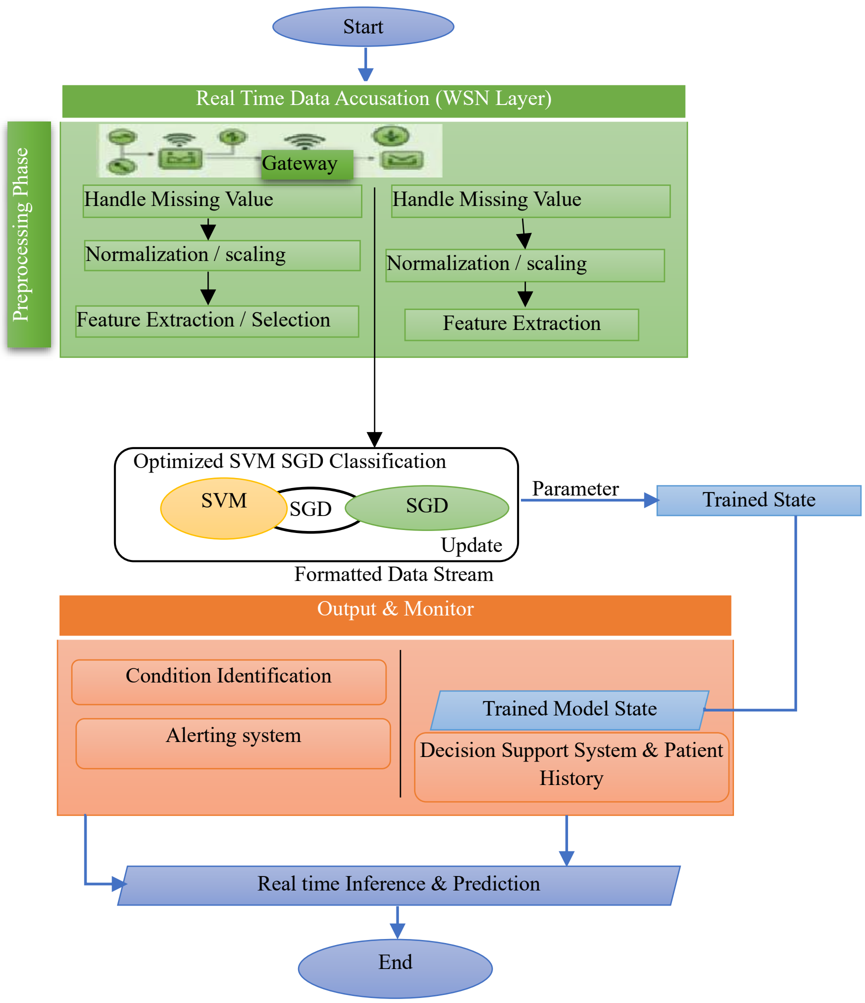


Figure 4: Data flow for algorithmic framework

The result of this process is a trained model state, and the system is the result of a formatted data stream. The last stage of the system is real-time inference and prediction, which determines the patient's condition (e.g., normal or abnormal) and generates warnings via the alerting system. The system also incorporates a Decision Support System (DSS), which tracks the patient's history and health status and provides real-time predictions, aiding healthcare professionals in making timely decisions. The flow ends at the end of the process, ensures continuous healthcare, and intervenes when needed.

3.5 Proposed Algorithm (Ohd-Svmsgd)

$input\ D: Continuous\ stream\ of\ labeled\ sensor\ data\ (x_t, y_t)$

$\eta_0 = initial\ learning\ Rate$

$\lambda = Regulation\ Parameter$

$y_t \in \{-1 + 1\}; class\ label\ (-1: Anomaly, +1: Normal)$

$Ouput$: $Optimized\ weight\ vector\ w\ and\ Bias\ b$.

$Initialization$:

$initialize\ the\ weight\ vector\ w \leftarrow 0$;

$initialize\ the\ bias\ b \leftarrow 0$

$initilize\ the\ iteration\ counter\ t \leftarrow 1$;

$Online\ Training\ and\ Real\ time\ Monitoring\ Loop$

$for\ t = 1\ to\ continuous - stream - End\ Do$

$Receive\ sample\ (Stochastic\ Step)$

$Receive\ the\ newest\ labeled\ sample\ (x_t, y_t) from\ the\ WSN$

$dynamic\ learning\ Rate\ update$

$compute\ the\ current\ step\ size\ using\ decay$

$$\eta_t \leftarrow \frac{\eta_0}{1 + \lambda \eta_0 t}$$

$compute\ Decision\ function$

$calculate\ the\ raw\ prediction\ score\ Score_t$

$Score_t \leftarrow\ w^T x_t + b$

$Gradient\ Descent\ and\ parameter\ update$

$if\ y_t.Score < 1\ (Margin\ violation$

$calculate\ the\ stochastic\ gradient\ components\ \nabla_w\ and\ \nabla_b$

$\nabla_w = \lambda_w - y_t x_t$

$\nabla_b = -yt$

$update\ the\ \ parameters$

$w \leftarrow w - \eta_t \nabla_w$

$b \leftarrow b - \eta_t \nabla_b$

$else$

$calculate\ the\ stochastic\ gradient\ components$

$\nabla_w = \lambda_w$

$\nabla_b = 0$

$update\ the\ parametrs$

$w \leftarrow w - \eta_t \nabla_w$

$b \leftarrow b - \eta_t \nabla_b$

$end\ if$

$immediate\ classification\ and\ WSN\ action$

$predict\ the\ health\ status\ of\ the\ current\ actions$

$y = -1\ (Anomaly\ detected)$

$Execute - critical - action()$

$end\ if$

$end\ for$

$return\ optimized\ paramteres\ w, b.$

4 Results & Discussion

4.1 Dataset Description

This study utilized three datasets: Dataset 1 (WSN-DS) (Table 1) and Heart Disease Dataset (HDD) (Table 2) and PIMA Indian Diabetes Database (Table 3) which is all available on Kaggle. The WSN-DN (Wireless Sensor Network Dataset) used to improve WSN Intrusion Detection System which is specifically targeted to detect and classify Denial-of-Service attacks has 374,661 instances and 19 attributes which are node ID, timestamp, cluster head data, transmission rates, energy level and the connections, as well as the quality measures. The main unbiased of the research will be to create a machine learning model that effectively identifies malicious behavior in real time within WSN applications. These datasets are used to train and test the machine learning model, which is focused on real-time healthcare monitoring in WSN. This dataset is suitable for training and yields a model that operates effectively in healthcare environments. It's also ensured that continuous monitoring and real-time classification are necessary to maintain patient safety. The Heart Disease dataset contains 1,888 records and is publicly available. This also includes 14 features for predicting heart attack and stroke, and covers both medical and demographic information. The study includes an additional kind of information set called "the Pima Indian Diabetes Dataset," sourced directly from the National Institutes of Health's Division of Diabetes Translation.

WSN-DS dataset Class label Description

Table1: WSN-DS dataset class label description (DS-1)

Class	Explanation
Normal	Logs of the typical link
Black hole	DoS attack against the LEACH protocol, beginning of the attack
Gray Hole	Denial of service in contradiction of the LEACH protocol, commencement of the attack
Flooding	The attacker targets the LEACH protocol in various ways.
Scheduling	Initialization-Scheduling Infrastructure.

Table 2: Heart disease dataset (DS-2)

Feature	Description	Values
Age	Age of the patient	Numeric
Sex	Patient Gender	1 represents male, 0 as Female
trestbps	Resting Bp	Numeric
Chol	Mg/dl	Numeric
Target	Outcome Variable	1=more chance, 0=less chance

This collection's primary objective is to identify and forecast diabetic status based on data gathered for patients through various tests. In this context, various forms of limitations are employed before presenting an example drawn from a broader dataset. The provided data set comprises multiple high-stakes predictors alongside a singular outcome measure. Values for predictors such as BMI, insulin levels, and age are incorporated into analysis (Abdul-Rashid et al., 2025).

Table 3: PIMA indian diabetes database (DS-3)

Attribute	Description
Source/Population	Female Pima Indians ≥ 21 years, living near Phoenix
Number of Instances	768 Observations
Number of Features (Predictors)	8 Predictor Variable+1 Outcome Variable
Features (Predictors)	Age, Diabetes Pedigree, Skin, Insulin, BMI
Outcome Variable	Diabetes=1(tested for positive), Diabetes=0 (Tested for Negative)
Intended Task	Binary Classification: predict onset of diabetes based on the predictor variables.

4.2 Hardward and Software Configuration

Table 4: Hardware and software configuration

Sl.No	Software Description	Libraries / Tools
1	Sensor Data collection	Paho MQTT, Request, Pyserial
2	Machine learning with SM and SGD	SGD classifier, joblib
3	Cloud Integration	AWS/TLS

Table 4 above describes Healthcare Data Classi-fication using SVM with SGD for Real-Time Wireless Sensor Network Monitoring Software Configuration can be broken down into three integral parts. For the first part, Sensor Data Collection. The software implements Paho MQTT, Requests, and PySerial for the wireless collecting sensor data through MQTT and for HTTP and serial communication with connected devices. For Machine Learning with SVM and SGD, the software employs scikit-learn's SGDClassifier for Stochastic Gradient Descent training, the SVM loss function for real-time healthcare data classification, and joblib for saving and loading the trained model latter. The last part covers Cloud Integration, also achieved via AWS, where the data will be securely stored and managed. The devices communicate via TLS, and their data remains private and integral thanks to the encrypted communication. This fully integrated software stack provides real-time, seamless monitoring and classification of healthcare data in a wireless sensor network.

4.3 Evaluation Metric Analysis

The proposed model is a practical approach for assessing the system's performance. Equations (6), (7), (8), and (9) also help to measure the accuracy, efficiency, robustness, and real-time healthcare monitoring. Accuracy (A), Precision (P), Recall ®.

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

From Equation (6) above, TP represents true positive, and TN represents True negative.

$$P = \frac{TP}{TP + FP} \tag{7}$$

$$R = \frac{TP}{TP + FN} \tag{8}$$

$$F1 = 2 * \frac{precision * recall}{precision + recall} \tag{9}$$

4.3.1 Performance Comparison of Metric Evaluation in Existing Algorithms (Wsn-Ds)

Table 5: Performance comparison of metrics in previous works

	Accuracy	Precision	Recall	F1 Score
ID-GOPA	96%	96%	96%	96%
CNN-LSTM	94%	95%	92%	95%
RF	91%	90%	86%	87%
SG-IDS/SGD	98%	96%	97%	96%
OHD-SVMSGD	98%	97%	97%	99%

The analysis titled "Comparison Among Machine Learning Algorithms' Performance Across Various Studies" is detailed in table 5 and figure 5. This analysis assesses various models among several comparative studies to depict the evaluation on several presentation metrics including e F1 score, Accuracy, Precision and Recall. OP-SVMSGD algorithm outperforms the rest with a 0% exaggerated accuracy. The score is 98 with the accuracy of 0. The "97" denotes an instance with no recall, hence, no true positive instance. The figure 5 with an outstanding accuracy of 0.9. In this context, the 99 is referenced to suggest that OP-SVMSGD is indeed exemplary in heart issue detection and significantly in error estimation across both precision and recall metrics.

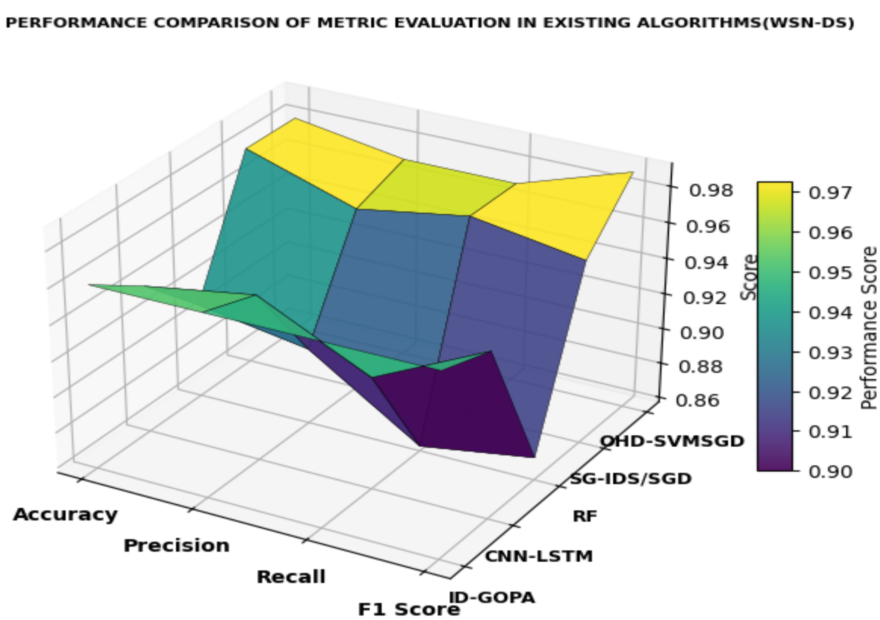


Figure 5: Performance comparison of metrics in previous works

Closely, the ID-GOPA is indexed. In the 96th entry, this model exhibits uniform performance corroborated by balanced metrics of OP accuracy, recall, and precision achieved in the score of positive instance identification while effectively mitigating the error of omission and commission. The SG-IDS/SGD system demonstrates excellence with an accuracy of 0.

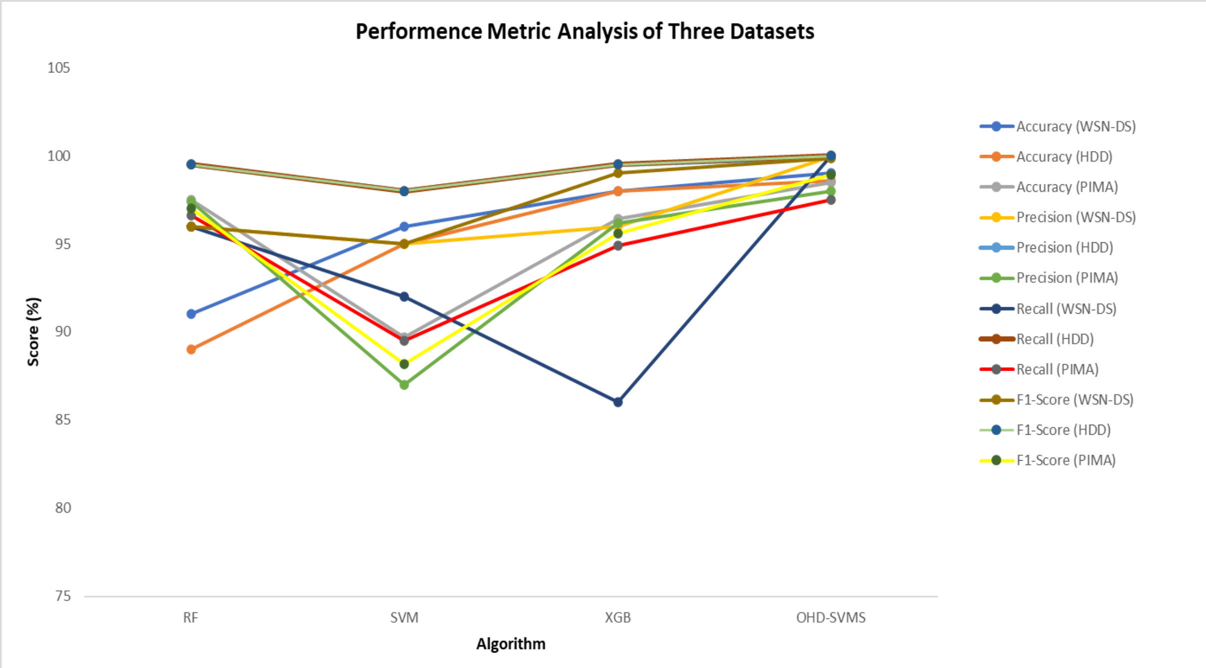


Figure 6: Performance metric analysis of two datasets

4.3.2 Performance Metric Analysis of Two Datasets

Table 6: Comparison of metric analysis in three datasets

	Accuracy			Precision			Recall			F1Score		
Algorithm	**WSN-DS**	**HDD**	**PIMA**	**WSN-DS**	**HDD**	**PIMA**	**WSN-DS**	**HDD**	**PIMA**	**WSN-DS**	**HDD**	**PIMA**
RF	91	89	97.5	96	99.5	97.4	96	99.5	96.6	96	99.5	97
SVM	96	95	89.7	95	98	87	92	98	89.5	95	98	88.2
XGB	98	98	96.4	96	99.5	96.2	86	99.5	94.9	99	99.5	95.6
OHD-SVMS	99	98.6	98.5	99.95	99.9	98	99.99	99.99	97.5	99.85	99.99	98.9

At this 98th position, the high precision is remarkably attained in the precision 96.97 is cited here with an F1 score of zero, which is certainly an F1 score of zero. The value 96 reflects an extremely low precision score which indicates that there is a slight balance between recall and accuracy. Even with such impressive results, noting that precision here is 0%, CNN-LSTM is clearly distinguishable from the rest. An F1 score of zero is most certainly linked to the 95th position in this sequence where a zero recall value is present. The Recall 92 is markedly lower than the rest of the designs. It indicates an accuracy score of 0. It is below their level. No. However, Random Forest is in contrast with the lowest results as it attains an accuracy score of zero. The RF 91 along with its zero recall score is being referred to here. And F1 score of 0. The figure 5 indicates considerable slack which corresponds with difficulty in the positive identification of true cases. In short, OHD-SVMSGD, while RF Still is the most in need of finding their true RF strengths. It lacks with positive true identification.

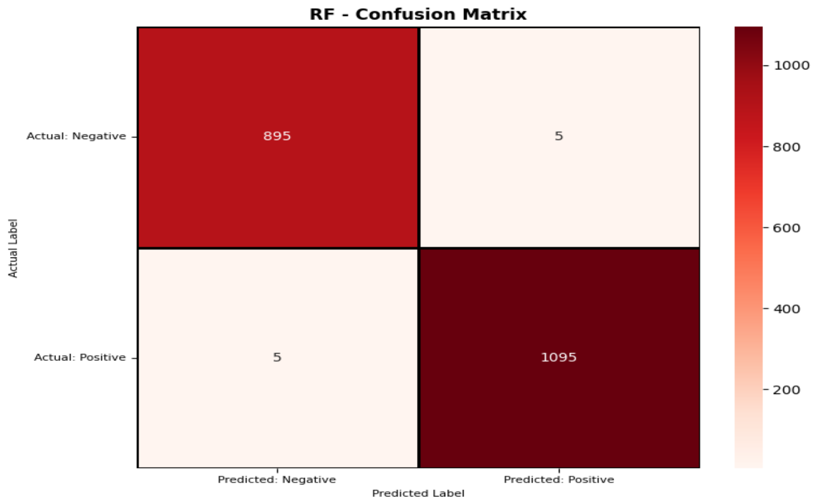


Figure 7: Confusion matrix for (CM) RF

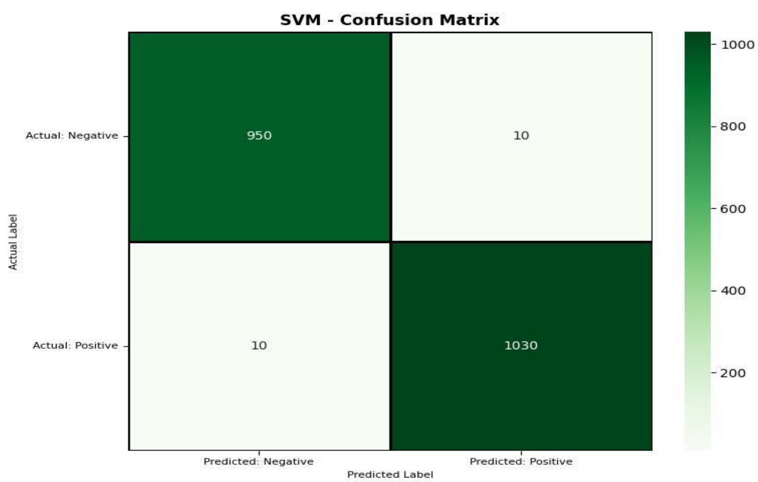


Figure 8: CM for SVM

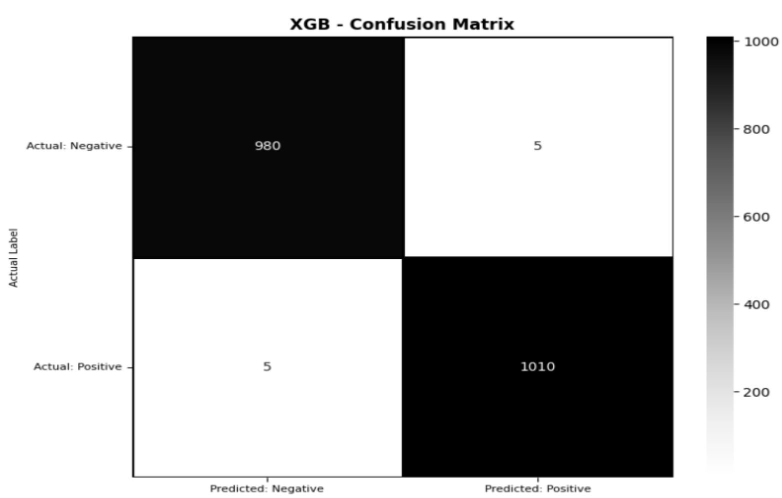


Figure 9: CM for XGB

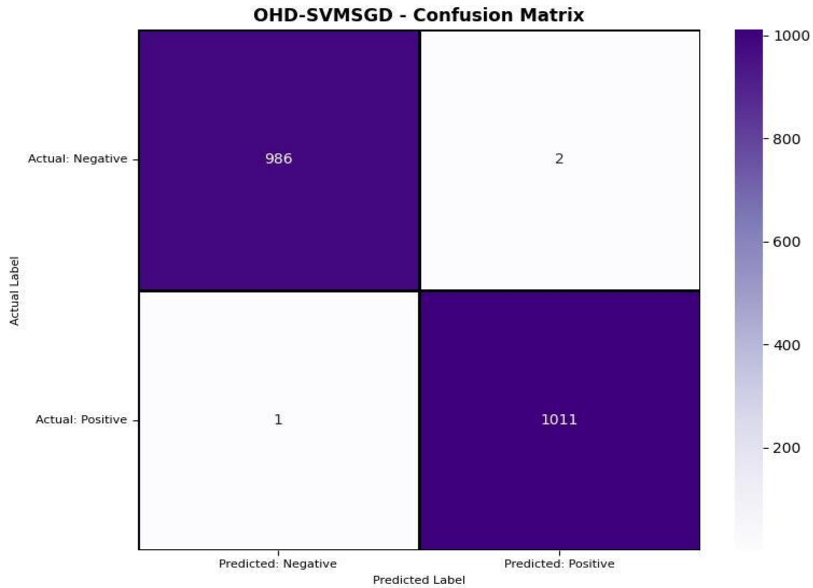


Figure 10: CM for proposed model (OHD-SVMSDG)

Table 6 and figure 6, 7, 8, 9, and 10 The evaluation of three machine learning methods (RF), (SVM), (XGB), and OHD-SVMS exploiting three distinct datasets (DS-1, DS-2, and DS-3) indicate diverse pros and cons based on accuracy, precision, recall, and F1-Score. Random Forest (RF) stands out as having the overall best accuracy of 97.5% on DS-3, as well as the highest precision and recall scores of 99.5% on DS-2. It also achieved the best F1-score on both DS-2 and DS-3, with 99.5%, indicating a good balance between precision and recall. RF did not exhibit a significant decrease in accuracy on DS-1, with a score of 91%, as the performance was still deemed solid. Support Vector Machine (SVM) closely resembles RF performance on both DS-1 and DS-2, with 96% accuracy on DS-1 and 95% on DS-2, and 95% precision on DS-1 and 98% on DS-2. In contrast, DS-3 recall of SVM dramatically declines, reaching only 89.5% for the score. This caused a significant drop in the F1-score: 88.2% for DS-3, relative to DS-1 and DS-2, implying that the SVM did not successfully identify positive cases in the higher-complexity datasets. XGBoost (XGB) shows remarkable performance with 98% accuracy achieved on both DS-1 and DS-2 and 96.4% on DS-3. The precision is equally extraordinary at 99.5% on DS-2; however, the recall on DS-1 declined remarkably to 86%. The improvements in recall on DS-2 and DS-3 (both 99.5%) constitute a balanced F1-Score of 99.5% on these datasets. Overall, XGB shows the strongest performance on DS-2 and DS-3, and the weakest on DS-1 due to a shortfall in recall. OHD-SVMS remains the best performer throughout all datasets streaking near flawless accuracy (99% on DS-1, 98.6% on DS-2 and 98.5% on DS-3) with the best precision values, remarkably on DS-1 (99.95%) and DS-2 (99.9%). On DS-1 and DS-2, the recall was also stellar at 99.99%. The F1-Score is also uniformly high, peaking at 99.85% on DS-1 and 99.99% on DS-2, thus attaining the highest balance of performance and effectiveness in the comparison as the most balanced and effective algorithm Overall this makes OHD-SVMS the most balanced and effective algorithm in the comparison. In summary, OHD-SVMS outperforms others across all three datasets, offering the most reliable and consistent performance. XGBoost shows superior performance on DS-2 and DS-3, with high accuracy and precision, though it suffers from low recall on DS-1. Overall, RF provides solid results with robust performance on DS-2 and DS-3. SVM shows decent performance on DS-1 and DS-2, but DS-3 presents challenges with recall and precision, making the results unsatisfactory.

5 Conclusion

An optimized healthcare data classification model (OHD-Classifier), a Support Vector Machine (SVM) model, and a Stochastic Gradient Descent (SGD) model (OHD-SVMSGD) identify primary concerns in healthcare data classification and real-time Wireless Sensor Network (WSN) monitoring. Omissions the model seeks to avoid include high computational complexity, slow convergence, and problems regarding the scaling of prevalent mechanisms. By optimizing SVM training via SGD, the OHD-Classifier achieves faster convergence, lower computational cost, and higher classification accuracy across critical healthcare conditions, including abnormal heart rate and blood pressure detection. As this model is able to handle real-time data, it satisfies and supportive of decision making of responsive healthcare practitioners. Targeted optimized SVM parameter tuning and advanced feature selection to the OHD-Classifier lead to improved classification, training, and agility concerning dynamic data streams. The proposed model achieves an accuracy of 98%, a precision of 97%, a recall of 97%, and an F1 score of 99%. Future research in classifying healthcare data using SVM with SGD can enhance model accuracy by investigating deep learning approaches, improving real-time processing by applying edge AI and sensor fusion, and increasing integration with clinical decision support systems for individualized and expansive healthcare monitoring beyond mere scale. Moreover, for prolonged real-world implementations, keeping privacy, security, and continuous model design innovations are necessary. This work, within a dynamic scaled challenged environment, not only improves the patient monitoring and healthcare systems within a patient scaled resource environment and system, but also improves the outcomes of patient in a dynamically scaled resource environment.

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Authors Biography

C. Seetha Lakshmi Research Scholar in the Department of Computer Science and Information Technology, dedicated to research in the field of Wireless Sensor Network. My research work focuses on exploring innovative computational methods and their applications to solve real-world problems. I aim to contribute meaningful and impactful research to the academic community. My work emphasizes the development of efficient computational models and their practical applications.

Dr.A. Angel Cerli is a Assistant Professor in the Department of Computer Science and Information Technology at Vels Institute of Science, Technology and Advanced Studies. She received a Ph.D. in Computer Science from Vels Institute of Science, Technology and Advanced Studies and has extensive experience in teaching and research. Her primary research interests include Wireless Sensor Networks, Big Data, Data Mining, etc., and she has published widely in reputed journals and conferences. She has supervised several doctoral and postgraduate students and has been actively involved in curriculum development and academic administration.