ENHANCING MILITARY HEALTHCARE RESPONSE WITH 5G-ENABLED SUPPORT VECTOR MACHINES HEALTH TRACKING SYSTEMS

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ABSTRACT

The healthcare sector is being revolutionized by integrating 5G with emerging technologies. This provides ultra-reliable low-latency communication (URLLC), enhanced Mobile Broadband (eMBB), and ubiquitous connectivity. Nevertheless, there is a need to improve situational awareness, reduce response times, and enhance survival rates in combat scenarios for the military. 5G-enabled Support Vector Machines Health Tracking Systems in military contexts would allow to achieve these. This study focuses on deploying wearable health tracking systems on soldiers. This enables continuous monitoring of vital signs such as heart rate, body temperature, blood pressure, and oxygen saturation while soldiers are on the battlefield. Thus, in this study, a 5G network health monitoring system based on a machine learning model within a MATLAB simulation environment to enhance military medical response capabilities was designed, simulated and evaluated. The collected data was transmitted in real time via 5G networks. Thereafter, the data was processed using Support Vector Machines (SVM) algorithms in MATLAB to detect anomalies and identify soldiers who are in need of urgent medical attention.

Keywords: Military health tracking system, 5G, Wireless sensor networks, Support Vector Machine algorithm, smart healthcare

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1. | Introduction

The integration of advanced technologies into healthcare has revolutionized the delivery of medical services. It leads to improved outcomes and operational efficiencies. Machine Learning (ML) is among the advanced technologies and it is a subset of Artificial Intelligence (AI). It has emerged as a transformative force (Memon *et al.,* (2025)). It involves among others the development and application of statistical models and algorithms that allow computers to learn and predict based on data. The algorithms can identify complicated patterns and relationships within complex datasets. These often surpasses human capabilities in tasks such as diagnostic accuracy and treatment personalization (Esteva *et al.,* (2019)).

ML applications have demonstrated significant potential across various domains in healthcare. Its algorithms have been employed to analyze medical images such as X-rays, magnetic resonance imaging (MRI), and computed tomography (CT) scans, and this helps in the early detection of diseases like cancer (McKinney *et al.,* (2020)). ML algorithms can highlight elusive glitches that may be unnoticed by radiologists to enhance diagnostic precision and enable timely interventions. It has been applied in predictive analytics to forecast potential outbreaks of infectious diseases, patient deterioration, and hospital readmission rates, and this allows healthcare providers to allocate resources more effectively and implement preventive measures (Obermeyer and Emanuel (2016)).

Progress in ML and inception of Fifth Generation (5G) wireless technology have opened up new possibilities for healthcare innovation. 5G technology offers substantial improvements such as higher data transmission rates, reduced latency, and increased connectivity capacity, over its predecessors (Zhou *et al.,* (2020)). These features of the 5G are beneficial for healthcare applications that require real-time data exchange and remote monitoring capabilities. 5G enables the seamless transmission of high-resolution medical images and supports telemedicine consultations in real-time, which expands access to healthcare services in underserved and remote areas (Zhou *et al.,* (2020)).

5G AI technology has changed the way health is tracked, making it possible to monitor vital signs in real time. Nowadays, wearable devices, embedded with all sorts of sensors, can be used to monitor heart rate, blood pressure, glucose, and oxygen levels. The data can then be transmitted via 5G networks to centralized systems where ML algorithms analyze it in order to detect anomalies, predict health events, and provide immediate applications to healthcare providers and patients (Dastres and Soori (2021)). The systems would facilitate health management and reduce the burden on healthcare facilities by minimizing unnecessary hospital visits and admissions.

The health and readiness of personnel are paramount in military settings since military operations take place in challenging environments where access to medical care may be limited. The capability to monitor soldiers' health in real-time and predict potential medical issues before they escalate is critical. Application of 5G-enabled health tracking systems with ML algorithms offers a solution to these challenges. By equipping military personnel with wearable devices that continuously monitor vital signs and other health indicators, medical teams can receive timely alerts about potential health issues, which enables prompt interventions that can prevent more severe outcomes (Abiodun *et al.,* (2018)).

Support Vector Machines (SVM) are among the ML algorithms that are effective in healthcare applications in constrained environments. They are used in various medical applications for disease diagnosis and prognosis among others. SVMs are employed to classify electrocardiogram (ECG) signals to detect arrhythmias, where they demonstrate high accuracy in distinguishing between normal and abnormal heart rhythms (Krittanawong *et al.,* (2017)). On the issue of military health monitoring, SVMs can be utilized to analyze the complex data streams from wearable devices, for the identification of patterns indicative of stress or health deterioration so as to facilitate early interventions (Ngwira (2021)).

The implementation of such advanced health monitoring systems in military contexts requires robust simulation and modelling to ensure their efficacy and reliability before deployment. MATLAB is a high-level programming environment that offers a comprehensive platform for modelling, simulating, and analyzing complex systems (Tiamiyu *et al.,* (2024)). It provides a range of tools and functions that are suitable for developing and testing ML algorithms such as SVMs. By leveraging MATLAB's capabilities, researchers and developers can create detailed simulations of 5G-enabled health tracking systems, assess the performance of those systems in different situations, and improve the algorithms to optimize accuracy and responsiveness (Chukwunweike *et al.,* (2024).

SVM based 5G-enabled health tracking systems is a huge step forward in healthcare technology because it is highly promising for enhancing health monitoring and response capabilities in military contexts, where timely and accurate medical interventions are crucial.

Military operations expose personnel to mental and physical stress in remote and unpredictable environments, which makes timely medical support a pressing issue. Traditional healthcare models and conventional health monitoring methods are inadequate in such risky settings, where real-time monitoring and early intervention are vital to prevent bad medical condition (Armarkar *et al.,* (2017)).

Wearable health tracking devices gives a solution by collecting vital physiological data. However, these devices need advanced communication systems and intelligent data processing tools to be effective in combat zones. 3G and 4G communication technologies are of high latency, which introduces delays that hinder rapid decision-making during decisive moments (Armarkar *et al.,* (2017)). It is problematic in military operations where real-time responsiveness can determine mission success or failure.

This constraint compromises situational awareness and slows down timely medical or tactical decisions. 5G's ultra-high bandwidth capabilities enable seamless transmission of large datasets such as high-resolution sensor outputs, video feeds, and drone surveillance, which allows for more informed and immediate responses; very unlike the existing systems with low bandwidth that hinders the efficient transfer of such data (Kurhe and Agrawal, (2013)).

Network congestion is another major issue in densely populated or active combat zones. Overloaded communication networks introduce data latency or disrupt health monitoring altogether. 5G overcome delays and disruption in communication using massive machine-type communication (mMTC). mMTC provides stable and high-volume connections between numerous devices to ensure uninterrupted monitoring and communication flow in high-traffic areas (Ting *et al.,* (2020)).

Fragmentation of military communication systems causes interoperability challenges when diverse platforms and devices struggle to coordinate. Flexible architecture of 5G improves system coordination for smoother coordination across units and better support for real-time health alerts and medical decision-making (Bajracharya *et al.,* (2023)).

Beyond communication infrastructure, the large volume and complexity of physiological data produced by wearable devices require advanced ML algorithms to interpret in real-time.

The ability of SVMs to handle non-linear and high-dimensional data efficiently is ideal for complex physiological data (Ngwira (2021)).

In the evolution of modern healthcare, ML has become a foundation in domains that demand high precision, rapid diagnosis, and personalized treatment approaches. ML involves the development of algorithms capable of learning patterns from data and making autonomous decisions without being programmed explicitly for each scenario. In healthcare settings, where data-driven decision-making can enhance medical outcomes and improve operational efficiency, these capabilities of SVMs are important (Obermeyer and Emanuel, (2016)).

Many ML algorithms-based applications, such as disease prediction, medical imaging diagnostics, drug discovery, clinical decision support systems, and personalized medicine, have been applied to various healthcare domains. These are ML algorithms like reinforcement learning, natural language processing (NLP) and deep learning. These tools help healthcare professionals to identify complex patterns in large datasets that might not be easily discernible using traditional statistical methods (Abiodun *et al.,* (2018)).

Predictive analytics is one of the most promising areas of ML in healthcare. In predictive analytics, algorithms process real-time or historical patient data to guess future health events. SVMs are used for disease classification tasks such as cancer detection, cardiovascular disease prediction, and neurological disorder analysis (Dastres and Soori (2021)). These predictive tools are relevant in emergency and military medical contexts, where rapid and accurate decision-making is important because they can significantly influence survival rates and treatment efficiency.

The integration of ML algorithms with 5G-enabled wearable devices allows for continuous, real-time monitoring of physiological parameters such as heart rate, body temperature, and oxygen saturation. When analyzed using ML models like SVM, these data streams can detect early warning signs of health anomalies and prompt for immediate medical attention even in battlefield. These kinds of systems can reduce response time, prevent escalation of medical conditions, and improve operational effectiveness in risky scenarios (Zhou *et al.,* (2020)).

ML offers a pathway toward scalability and improved medical service delivery for healthcare systems operating in resource-constrained environments. Shortages of skilled medical personnel and limited access to advanced diagnostic tools can be resolved using intelligent, algorithm-driven support systems. ML supports clinical workflow optimization by assisting healthcare providers to manage medical records and triage patients. ML algorithms are applied to detect and manage conditions like malaria, tuberculosis, and HIV/AIDS, with complex diagnostic processes that benefit from automated and scalable support systems (Ginsburg *et al.,* (2018)).

5G-enabled SVM is unlocking potentials in telemedicine and remote health monitoring in military scenarios. Soldiers deployed in hostile or remote environments benefit from non-intrusive health surveillance systems that are powered by wearable devices and ML-driven anomaly detection. This enhances personnel safety, enables proactive intervention, and maintains combat readiness through real-time physiological monitoring and analytics (Krittanawong *et al.,* (2017)).

Usage of 5G-enabled SVM in a distinct and high-pressure conditions offers significant benefits by enhancing diagnostic precision, optimizing treatment plans, and ensuring efficient resource management (Abiodun *et al.,* (2018)).

The challenges of limited access to specialized healthcare personnel and outdated equipment are mitigated by enabling automated decision support, streamlining administrative tasks, and enhancing clinical outcomes using predictive analytics of ML. In emergency, ML models can facilitate real-time decision-making by ensuring timely care to improve survival rates (Esteva *et al.,* (2017)).

Healthcare system, which was originally limited to data analysis and electronic health record management has evolved noticeably in recent years by using ML (Ngwira (2021)). Now, ML plays a pivotal role in disease prediction, medical imaging, and personalized care delivery.

ML implementation in constrained military healthcare environments has several challenges despite its transformative potential, The challenges include poor data availability, limited access to advanced computing infrastructure, insufficient regulatory frameworks, and a lack of skilled personnel (Abiodun *et al.,* (2018)) and Wahl *et al.,* (2018)).

Eliyaz *et al* (2020) were able to track the location of the remote soldier using GPS. They used GSM technology to send all information to the army command unit for the necessary action to be taken.

Archana *et al.,* (2020) proposed a system that is capable of collecting and processing the physiological parameters from the human body. They concluded that when the normal body parameters differ from threshold values, an alert message/email is sent to the base station along with the exact location of the soldier.

The technique described by Kurhe and Agrawal (2013) allowed soldiers to be tracked at any time. When in distress, the soldiers would be able to use GPS coordinate information to communicate with the control unit. Through the use of body sensor networks, the army control unit would keep an eye on troops' vital signs, such as their body temperature and heart rate. GSM, or precisely 2G (second generation of networks), was used to wirelessly send the soldiers' parameters.

A "Soldier Health and Position Tracking System" utilizing barometric pressure sensors, GPS, GSM, and WBASNs (heartbeat sensor, temperature sensor) was proposed by Archana *et al.,* (2020). For their prototype, the ATmega328p microcontroller was utilized. Without any ML or training, basic conditional statements were utilized to determine the soldier's health. Using GSM, a message with the soldier's health status was transmitted at regular intervals; however, it was not practical in high-altitude locations where network connectivity was difficult.

Authors, Chakravarth *et al.,* (2017) were able to transmit the data which was sensed from a remote soldier to the server PC using wireless transmission technology GSM. The authors claimed that the environment around the mobile soldier unit, the GPS receiver, affected the system's precision.

LeCun *et al.,* (2015) also stressed the importance of overcoming data scarcity and improving data quality to ensure robust and generalizable ML models. The authors concluded that without high-quality datasets and robust data pipelines, ML systems may fail to deliver reliable outcomes in military healthcare.

Nevertheless, real-world deployment of SVMs with 5G-based systems in dynamic military environments is logistically demanding. Hence, using simulation platforms like MATLAB offers a practical alternative to design, test, and refine 5G-enabled SVM health tracking systems under controlled scenarios before live deployment.

By leveraging 5G communication and SVM algorithms within a MATLAB simulation framework, this research bridges the gap between continuous soldier health monitoring and the technical limitations of current communication and analytical systems to enhance military medical readiness and ensure timely, data-driven interventions under the most demanding operational conditions.

The outcomes of this study enable early detection of health anomalies to prevent medical emergencies during operations and reduce the burden on military medical personnel through automated diagnostics powered by ML. Furthermore, this research contributes to the broader field of health informatics and smart healthcare by demonstrating how advanced technologies can be used to provide scalable, intelligent, and effective healthcare solutions in constrained and high-stakes environments.

2 | Methodology

The study focuses on structuring the data to optimize performance within a 5G-enabled health tracking framework that is integrated with SVM algorithms in MATLAB. The pre-processing phase includes data cleaning, normalization, feature extraction, and dimensionality reduction. Processes of eliminating inconsistencies, minimizing noise, and ensuring that the data conforms to the formats required by SVM-based classification models are important. So, the data analysis process was systematically organized to ensure interpretable and robust outcomes. Figure 1 shows the flowchart of processes involved in this study.

The steps (Figure 1) are shown in the flowchart, and included:

i. Data Collection

The dataset, titled «Human Vital Signs», was sourced from Kaggle (link to dataset) for the study. It was based on an available dataset rather than

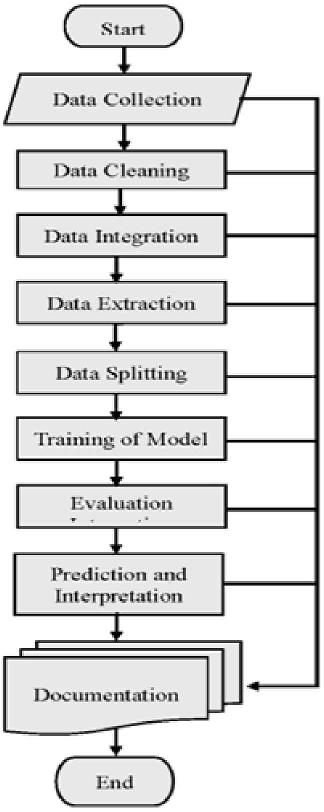


Figure 1 | Work Flowchart

field surveys or questionnaires (Arri (2022)). The dataset simulates real-world medical telemetry data captured through wearable sensors in 5G-enabled systems. The data was used to train and evaluate an SVM algorithm in MATLAB. This forms the core of the study's predictive modelling approach.

The dataset provided a reliable foundation for applying supervised ML techniques, the SVM, to develop a predictive health-monitoring model tailored for military applications.

ii. Data Cleaning

Duplicate records were removed from the dataset. Thereafter, the missing and inconsistent values were handled, and variable formats for key indicators, which are temperature, pulse rate, and oxygen saturation were standardized to ensure high-quality inputs for the SVM model.

Normalization techniques, which is important for the effective functioning of distance-based algorithms, were also implemented to ensure systematic scaling of all features.

iii. Data Integration

Data integration focused on organizing the dataset into a format compatible with ML toolboxes of MATLAB. Features were selected and engineered based on their relevance to predictive health analytics, and optimized for accurate classification and early warning detection.

These pre-processing steps were important to enabling the SVM model to identify health conditions, predict risks, and support timely decision-making within a 5G military health tracking system.

Data were transformed by standardizing variable formats, transforming categorical data into numerical representations, and generating new features through feature engineering. For example, features such as heart rate, temperature, oxygen saturation, and respiratory rate were normalized to enhance compatibility with the SVM algorithm.

iv. Data Extraction

Feature engineering was used to extract meaningful indicators and patterns that could improve model prediction. The dataset was formatted to conform to MATLAB's requirements for SVM training and testing to ensure the data structure supported accurate classification and analysis. These transformations contributed to improving the model's performance and its potential for real-time deployment in military health monitoring systems.

The population for this study is represented through anonymized data entries within the Kaggle dataset. These data points simulate potential real-time health monitoring subjects in defense or emergency response operations, where rapid and accurate health assessments are important.

Entries with missing or null values in any of the key health indicators were excluded during pre-processing to ensure model reliability. Also, duplicate records were removed to avoid skewing the performance metrics. A total of 1,307 instances were included in the dataset, each representing a unique set of vital signs.

v. Data Splitting

For model validation and generalization, the dataset was split in ratio 70:30 as training and testing subsets respectively.

vi. Training of Dataset

Applying the SVM algorithm to the training set, the model was trained to classify and forecast health risks based on biometric inputs.

vii. Model Evaluation

The performance of the SVM model was evaluated using standard metrics such as accuracy, precision, recall, F1-score and confusion matrix, which helped assessing the effectiveness of the model in supporting real-time health monitoring systems in military settings.

viii. Prediction and Interpretation

Using the trained model, the health conditions were predicted and the performance was interpreted.

ix. Documentation

Each step (Figure 1) was recorded for reproducibility and future reference.
Utilizing performance indicators, the trained model is judged for accuracy and potency in identifying the best path.

Functional efficiency of the system is evaluated using a dataset, which represents various 5G-enabled health tracking devices on military personnel, taken as a node. These nodes collect biometric data, like heart rate, temperature and blood pressure. The collected data are streamed to the system for analysis.

The evaluation focuses on the system's efficiency and accuracy in processing the health data and optimizing the military health response in real-time. Several performance metrics are employed to assess the system's capabilities. They are:

i. Processing Speed (to know how fast the system processes data from multiple nodes in real-time).

ii. Prediction Accuracy (to assess the system's capability to predict health conditions and emergency response needs).

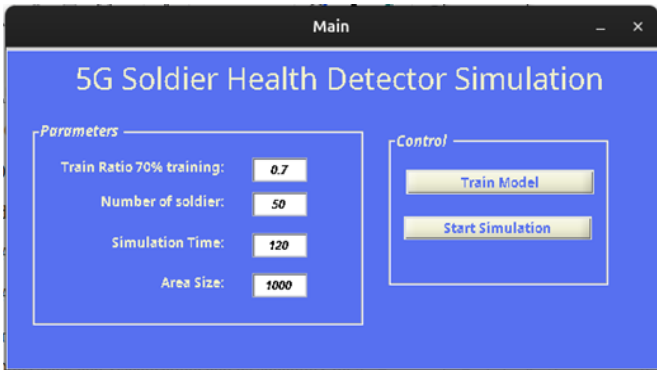
iii. Optimization Effectiveness (to find out how well the system allocates resources such as medical personnel, equipment in response to the real-time data).

iv. Scalability (to know the possibility of the system to handle increasing amounts of data as more nodes are deployed.

After the design phase, iterative refinements were made to ensure the accuracy and efficiency of the system and also to reduce programming errors and logical inconsistencies. Dataset pre-processing is vital in any ML method and was rigorously conducted to ensure the reliability of the predictive models developed.

The pre-processing steps were carried out using built-in functions (e.g. fillmissing, normalize, and fitcsvm) of the MATLAB for SVM model training. The study ensured that the SVM could effectively classify health conditions in a simulated 5G-connected military healthcare setting by preparing the dataset methodically. Figure 2 shows the interface of 5G-enabled SVM soldier health detector simulation model.

By clicking on the Train Model button, in Figure 2, the data is pre-processed and the model is trained. During dataset pre-processing, several typical data conversion scenarios were addressed to ensure data compatibility with the SVM model in MATLAB.



Train Ratio 70% training: 0.7
Number of soldier: 50
Simulation Time: 120
Area Size: 1000

Figure 2 | 5G-enabled SVM Soldier Health Detector Simulation Model Interface

They are:

i. Categorical Data, which is often represented as string values, were transformed into numerical formats using label encoding.

ii. Numerical Data as String. Some numerical values were converted and stored as strings due to either data entry inconsistencies or formats. These were parsed and converted into numerical types to allow for mathematical operations.

Feature selection played an important role in this study. It enhances the effectiveness and efficiency of the SVM model used to predict and classify soldier health conditions based on biometric data transmitted through 5G-enabled sensors.

Functions and custom scripts in MATLAB were used to implement feature selection, while statistical and algorithmic approaches such as recursive feature elimination (RFE), univariate selection, and correlation analysis were used to compute faster, reduce overfitting, enhance interpretability, and improve model performance.

70% of the cleaned and preprocessed dataset was used to train the SVM model, while the remaining 30% used to evaluate the model's ability to generalize on unseen data. The *fitcsvm* function in MATLAB was used for model training, while *predict* was employed for classification on the test set. The performance of the model is then assessed by comparing the outcomes with the real values. Assessing the model, metrics like ROC curves, confusion matrices (True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)), accuracy, precision, recall, Cohen's kappa score and F1 score are employed for SVM classification tasks. Also, Flexible Data (FD) rate and Flow Optimization (FO) rate are employed to balance classification accuracy with the speed required for real-time data processing.

3 | Results and Discussions

The ROC curve (Figure 3) depicts the actual positive rate (recall) versus the FP rate at different threshold values. Table 1 shows the metrics employed and input/resulted values for model training. Cohen's kappa score of 93% indicates the model's accuracy is nearly perfect. Flexible Data (FD) rate of 0.0144 indicates that the environment is highly constrained. The Flow Optimization (FO) rate of 0.056 leads to faster initial convergence which allows the model to take larger steps during optimization.

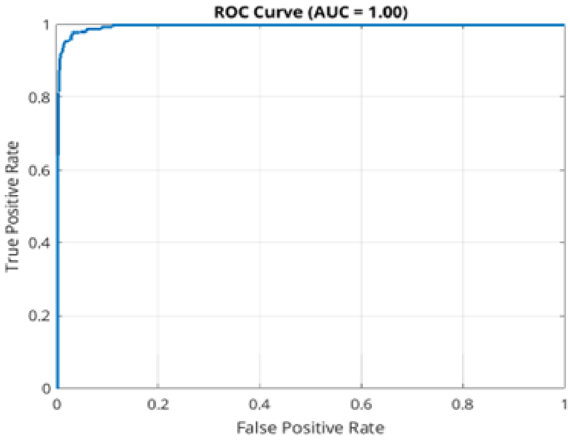


Figure 3 | ROC Curve

The Area Under the ROC Curve (AUC) represents the degree of separability (Figure 3). A greater AUC indicates a better model.

Table 1 | Metrics Employed and Input/Resulted Values for Model Training

Metrics	Input/Resulted Values
Accuracy	0.98
Precision	0.95
Recall	0.94
F1 score	0.95
True Negative rate	0.99
False Negative rate	0.056
Flexible Data rate	0.0144
Flow Optimization rate	0.056
True Positive	1658
True Negative	5807
False Positive	85
Cohen's kappa score	0.93
Trained Time	8.468795

An F1 score of 0.95 indicates that the model achieved an excellent balance between precision and recall. The recall rate of 0.94 and Precision of 0.95 (Table 1) show that the model successfully captured most positive cases while making very few false positive errors.

Figure 4 shows the prediction results (the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)). TP is the count of instances where the model correctly predicted the positive class while TN count signifies the number of times the model unmistakenly predicts a negative output. Instances when the model mistakenly predicts a negative output are referred to as FN, whereas FP is when the model mistakenly predicts a positive output.

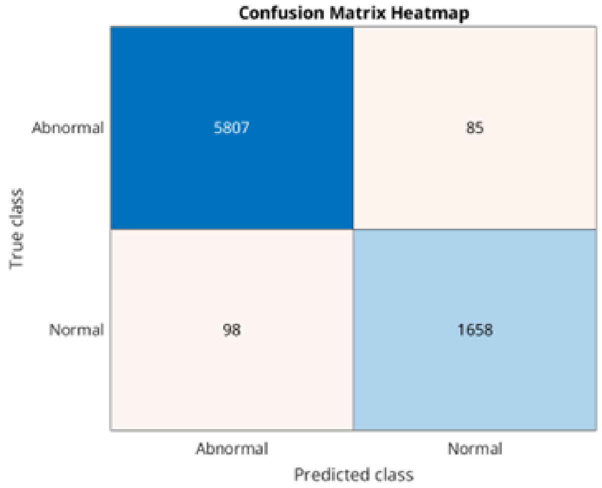


Figure 4 | Prediction Results

Table 2 and Figure 5 show the simulation results for 50 soldiers. According to the table, 18 soldiers are healthy, while the remaining 32 have some health issues.

Table 2 | Simulation results for 50 soldiers

Number of soldier's	Number of Normal Health (No issue)	Number of Abnormal Health (With issues)
50	18	32

Figure 5 shows the base, healthy soldiers (green colour) and unhealthy soldiers (red colour).

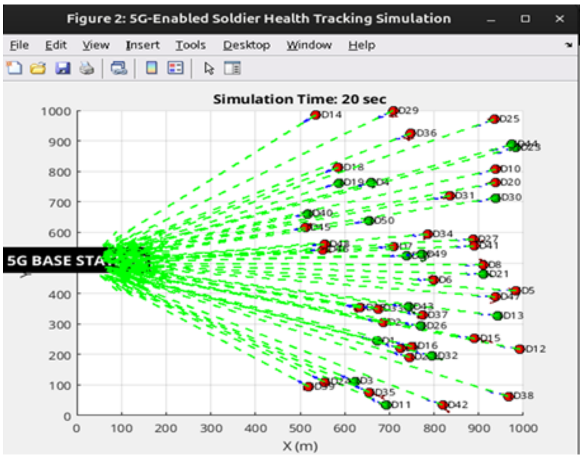


Figure 5 | 5G-enabled Soldiers' Health Status Tracking Simulation

Figures 7, 8 and 9 show Latency, Packet-loss and Throughput, respectively, as obtained from the simulation results.

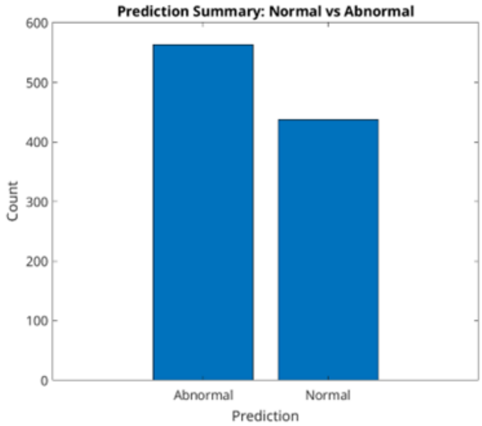


Figure 6 | Prediction summary

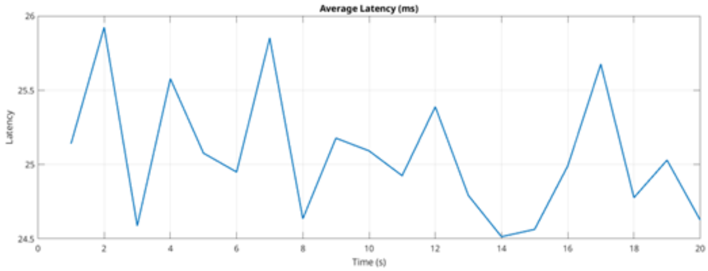


Figure 7 | Latency

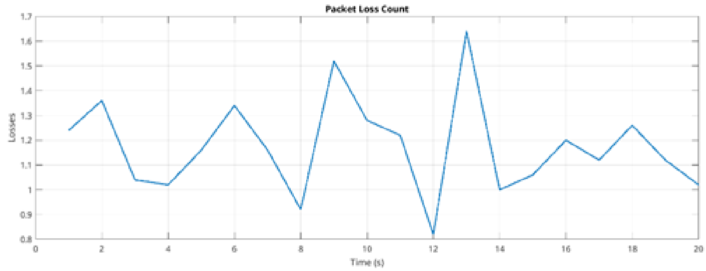


Figure 8 | Packet-loss

As seen in Figure 7, the 5G latency range is less than 26ms. This reduced delay is crucial for the military healthcare system as it enhances situational awareness and reduces response times to issues in the field.5G packet loss rates, though, vary significantly. As observed in Figure 8, the packet loss is generally low. This is good, as high data packet loss rates threaten the reliability of military operations. It could disrupt critical communication.

The throughput is in the range of 48.4 packets/sec and 52.8 (Figure 9). The actual rate is affected by factors such as location, signal strength, and network congestion. Though this throughput range is very low for modern, data-intensive military operations, it is sufficient for text/voice communications in constrained environments, the kind being considered for this study. Moreover, the wearable sensors used in this study (photoplethysmography (PPG), skin temperature sensors, GPS trackers, etc.) generate small amounts of data at infrequent intervals or in continuous, low-rate streams. Thus, there is no demand for high data speed (throughput).

Figure 10 shows the serious conditions detected.

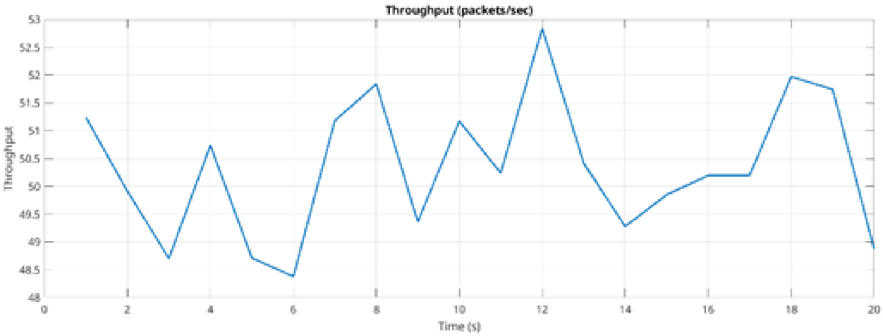


Figure 9 | Throughput

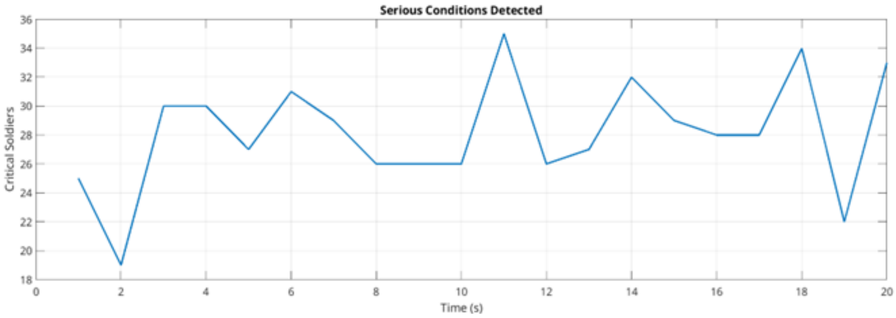


Figure 10 | Serious conditions detected

The use of SVM classifiers successfully identified soldiers experiencing abnormal physiological conditions such as shock, dehydration, or cardiac stress (Figure 10), and **r**eal-time alerts enabled command units to quickly locate and respond as fast as possible to the injured or distressed soldiers (Figures 6 and 7), thus improving survival chances during golden hour windows. Also, by prioritizing attention to those in critical need (Figure 5), the system reduced unnecessary deployments of medical teams, thereby conserving valuable resources and manpower.

4 | Conclusion

The study demonstrated the viability and crucial significance of integrating ML and 5G technologies for real-time soldiers' health tracking on the battlefield. SVM-based classification achieved a high accuracy of 98% (Table 1), when trained on simulated battlefield health data. This indicates strong potential for real-world application.

Very unlike traditional hospital-based healthcare, the model allowed continuous monitoring of vital signs on the simulated battlefield. The 5G-enabled SVM algorithms detected anomalies and identified soldiers who are in need of urgent medical attention. Thus, improving situational awareness, reducing response times, and enhancing survival rates for soldiers in resource-constrained and high-stakes battlefield environments using 5G-enabled SVM Health Tracking Systems, military healthcare can be revolutionized and enhanced.

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