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PAPER

A Real-Time Heart Attack Detection and Warning System for Drivers Using Neural Network

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ABSTRACT

The high rate of vehicle accidents is a major cause for concern, especially those caused by drivers suffering heart attacks while driving. Such accidents lead to a tragic loss of life and significant material damage, posing a serious threat not only to the drivers themselves but also to everyone with whom they share the road. Several solutions have been proposed to identify heart attack risk factors among drivers, but they have proven to be inadequate and lack accuracy and speed. In addition, these methods often require drivers to perform complex tasks during a heart attack due to the complex procedures involved in the examination process. This study determines the design of a system capable of identifying the heart attack risk areas. It also implements an alert mechanism that can save the life of a driver who has a heart attack while driving and at the same time reduce the risk of accidents involving pedestrians or other drivers. The system starts by recognizing the driver through a camera inside the car, then makes a quick check by collecting data from sensors and wearable devices such as heart rate, body temperature, and blood pressure, then processes it to detect possible heart attack risks in a non-surgical and cost-effective way. The Max30100 sensor is used to collect heart rate and blood oxygen levels, while the MLX90614 sensor captures body temperature. The ESP32 board acts as a bridge connecting the sensors to the Jetson Nano board. Blood pressure data is collected through wearable devices. Then all this data is processed using a Neural Network (NN) algorithm, which is implemented on an intelligent microcontroller built into the Jetson Nano board. The warning system is triggered if the algorithm determines that the user is at risk of a heart attack. The system was evaluated using a dataset created specifically for this study by collecting data for 1467 real cases, some of which suffered heart attacks, others did not experience problems with the change in their vital symptoms. A comparison was made between the SVM, random forest, logistic regression, and NN algorithms using Python. Used 20% for validation, the metrics using F1 score, recall, precision, and accuracy, which achieved 99.2% on the NN algorithm.

KEYWORDS

Neural Network (NN), heart attack, machine learning algorithms, heart dataset

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1 INTRODUCTION

Road traffic accidents are one of the leading causes of deaths and injuries in the world, resulting in not only the loss of precious human lives but also affecting economic resources. According to the World Health Organization (WHO), over 1.35 million people are killed, and over 50 million are injured due to road accidents throughout the world [1]. A large number of accidents occur due to drivers suffering from heart attacks and losing control of their vehicles. Heart attack, also known as a Myocardial Infarction (MI), is a serious medical emergency in which blood flow to the heart is suddenly blocked, usually by a blood clot in a coronary artery, it ranks as one of the largest causes of death and disability around the world [2].

Even though a heart attack is life-threatening, it has early symptoms that could greatly help in saving many lives and avoiding consequences if it's detected and reported promptly to healthcare facilities. A smart monitoring system can detect early signs of a driver's heart attack to prevent accidents and provide medical assistance in time [3]. Most healthcare monitoring systems, like neural network algorithms, depend on machine learning algorithms to analyze medical data.

Neural networks is one of the machine learning algorithms that have played a significant role in the medical field due to their ability to simulate health-related studies effectively. They are utilized for tasks ranging from analyzing datasets and diagnosing symptoms to assisting professionals in making informed decisions [4]. These algorithms are specifically designed for dataset analysis.

Heart-related datasets include the NTHU-DDD dataset, which is used for machine learning classifier training and facial feature extraction [5], and the UTA-RLDD dataset, which employs computer vision technology to detect visual indicators of abnormal driver conditions [6]. Many researchers differ among themselves in terms of processing and storing datasets. Whether the processing is done locally, on the cloud or conducting processing and storage operations on the cloud depends on the nature of the system. In any scenario, leveraging cloud storage offers significant benefits by providing a range of advantages directly.

Cloud storage is an essential aspect of cloud computing, providing users with a range of features such as automatic backups, data synchronization, collaboration tools, scalability, and cost-effectiveness. With cloud storage, users can easily store and access their files and data from anywhere using any internet-connected device, eliminating the need for physical storage devices and significantly reducing the risk of data loss or corruption [7].

2 BACKGROUND AND RELATED WORKS

2.1 BACKGROUND

The application of ML technologies has a significant impact on the development of intelligent systems to detect heart attacks effectively. ML models can extract both hidden correlations and patterns that support accurate prediction of heart attacks by making use of large-scale clinical and diagnostic datasets [8]. Due to the large number of road accidents associated with sudden heart attacks, the prediction of heart attacks among drivers has become a vital area of research. Advances in advanced surveillance have become a necessity, whether through sensors or wearable devices and combining them in order to continuously collect and evaluate physiological parameters in real time. This integration facilitates the proactive identification of heart attacks, thereby reducing emergency response time. Promising results in terms of accuracy and sensitivity have emerged through investigations; however, concerns remain about data confidentiality, sensor reliability, and wider validation requirements across different populations and environmental conditions [9]. Among the various ML models, NN have emerged as a reliable tool used for modelling complex and nonlinear data structures and simulating some cognitive functions of the Human Brain, Learning Representations and inferring relationships from experimental data. It has proven effective in areas such as pattern recognition and self-control [10] [11]. NN architectures are described in Figure 1. The prediction is influenced by many design and operation factors, including network topology, parameter initialization, learning algorithm, training dataset configuration, and learning rate [12] [13].

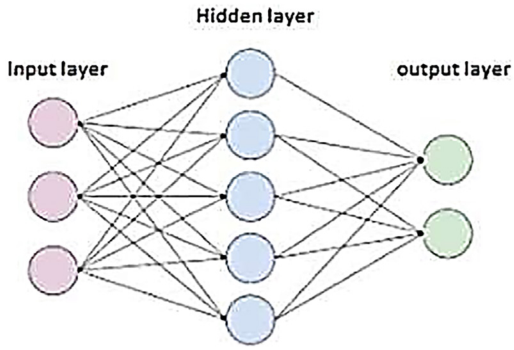

Fig. 1. NN architectures [12]

The performance of NN is dependent on several factors, such as the topology of the NN, initial structure, training method, input and output representations, learning rate, and the content of the training sample [12] [13]. Reverse error propagation remains the most widely adopted training methodology due to its ability to optimise iteratively and its effectiveness in reducing prediction error [14]. Moreover, activation functions such as sigmoid, ReLU, Tanh, and SoftMax enhance the network's ability to capture non-linear dependencies and improve Model expression. Complementary optimisation (solution) strategies are used to adjust weights and biases to enhance the accuracy and generalizability of the trained model [15], [16].

Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), play a crucial role in health monitoring and real-time applications. CNNs are particularly valued for their exceptional performance in analysing image data, making them ideal for medical imaging tasks such as disease detection and segmentation. On the other hand, RNNs are effective in handling time series data, which is essential for systems requiring continuous health monitoring. These NN models significantly improve the accuracy and efficiency of health diagnosis and patient care [17].

The IoT infrastructure in heart monitoring systems enables real-time data collection and transmission through sensors and wearables. This data is stored and analyzed in the cloud, allowing healthcare providers to monitor patients remotely. The system enhances patient mobility and ensures continuous, proactive healthcare management.

The IoT infrastructure used in heart attack monitoring systems enables real-time data collection and transmission through sensors, wearable devices, and smart boards, and the available storage tools, whether local or cloud, have helped to ensure data analysis in a way that ensures the delivery of excellent and remote health care. By allowing data to be stored on remote servers via the Internet, cloud technology eliminates the need for expensive local hardware, making it a cost-effective and scalable solution for managing the vast amounts of data generated by IoT-enabled heart attack monitoring systems.

Cloud technology allows users to store data on remote servers via the Internet, eliminating the need for expensive hardware. This scalable approach offers flexibility and automates backups, saving time and reducing stress. Cloud services include Infrastructure as a Service (IaaS, Platform as a Service (PaaS), and Software as a Service (SaaS). While it provides benefits such as disaster recovery and lower system failure risk, it also poses security challenges such as unauthorized access and data breaches. Major providers include Amazon Web Services (AWS), Microsoft Azure, and Google [34].

2.2 Related works

Al-Sheikh and Ameen [18] developed a mobile healthcare monitoring system using IoT and cloud computing for remote bio-signal monitoring (ECG, heart rate, SpO2, and body temperature). It employs Arduino and NodeMCU for data transfer and Blynk for live monitoring. The system's accuracy is verified against medical devices. Limitations include reliance on Wi-Fi and device compatibility. Challenges involve integrating multiple health parameters and ensuring data security and privacy through robust encryption.

Naik and Sudarshan in [19] developed a mobile healthcare monitoring system using IoT and cloud computing for remote bio-signal monitoring (ECG, heart rate, SpO2, and body temperature). It employs Arduino and NodeMCU for data transfer and Blynk for live monitoring. The system's accuracy is verified against medical devices. Limitations include reliance on Wi-Fi and device compatibility. Challenges involve integrating multiple health parameters and ensuring data security and privacy through robust encryption.

The study of Patel et al. [20] aims to develop an IoT-based system for heart attack detection and heart rate monitoring. The system uses sensors to collect heart rate data, which is processed and transmitted via IoT to healthcare providers. It successfully detects heart attacks and monitors heart rates, providing real-time data to healthcare professionals. Limitations include reliance on continuous internet connectivity and compatible devices. Challenges faced involve integrating multiple health parameters and ensuring data security and privacy through robust encryption.

Nancy et al. [21] proposed an IoT-cloud-based smart healthcare system for heart disease prediction using deep learning. It employs Bi-LSTM to analyze data from IoT devices and electronic clinical records stored in the cloud. The system achieves high accuracy (98.86%) in predicting heart disease. Limitations include reliance on continuous internet connectivity, and compatible devices, and the challenges faced by authors involve integrating multiple health parameters and ensuring data security and privacy through robust encryption.

Arjunan and Joseph proposed in [22] a wearable sensor system to monitor the health status and fatigue levels of automobile drivers. It uses a camera and various sensors to capture real-time video and health parameters, with a feature extraction module and fatigue analyzer. The system successfully monitors driver's health and fatigue, providing warning signals when thresholds are exceeded. The proposed system faced some limitations, including reliance on continuous power and potential privacy concerns. Challenges faced involve integrating multiple sensors and ensuring accurate real-time analysis and feedback.

Farhan et al. [49] During the COVID-19 outbreak, all societies around the world were able to keep using technology or apps. Using technology for our daily events and live.

Almaiah et al. [50] Discover the key factors that effect on adoption of mobile-government services. As a result, the study identified the critical factors that influence users to adopt the system and developed an integrated model as a powerful tool that assists in the adoption process of mobile government applications.

Al-Saqqa et al. [51] highlights how to choose the best suitable agile methodology that must be selected according to the task at hand, how sensitive the product is and the organizational structure.

This study proposes an intelligent system for determining the heart attack risk area for drivers in real-time by connecting IoT tools and analyzing their input using the NN algorithm. The system was distinguished by the ease of conducting the inspection process in real-time for several reasons, including the effectiveness of the IoT tools used, their diversity from cameras, sensors, and mobile devices, ease of handling to the flexibility of storing multiple data, and diversity in their options, down to the data set built specifically for it, which includes new features that helped improve the actual response time of the inspection process, because it relied on adding the satisfactory record of the driver and thus the speed of comparing the entered data with the stored data about the driver himself. The process of obtaining results was carried out using two methods, the first is experimental, using the Orange tool program to compare the accuracy of NN with other machine learning algorithms, and Visual Studio simulation with Python to obtain accurate results.

3 METHODOLOGY

The primary focus of developing the system in this work center is on designing its stages, including data collection, data preprocessing, analysis, and the implementation of the warning system.

3.1 Data collection

The data collection stage serves as the foundational and initial step in evaluating the effectiveness of the proposed system. Technology holds significant potential for various medical applications and purposes. As illustrated in Figure 2, the data collection phase has been completed. The proposed system integrates both hardware and software components, including a camera (PiCam360), a pulse sensor (MAX30100), a temperature sensor (MLX90614), and wearable blood pressure devices.

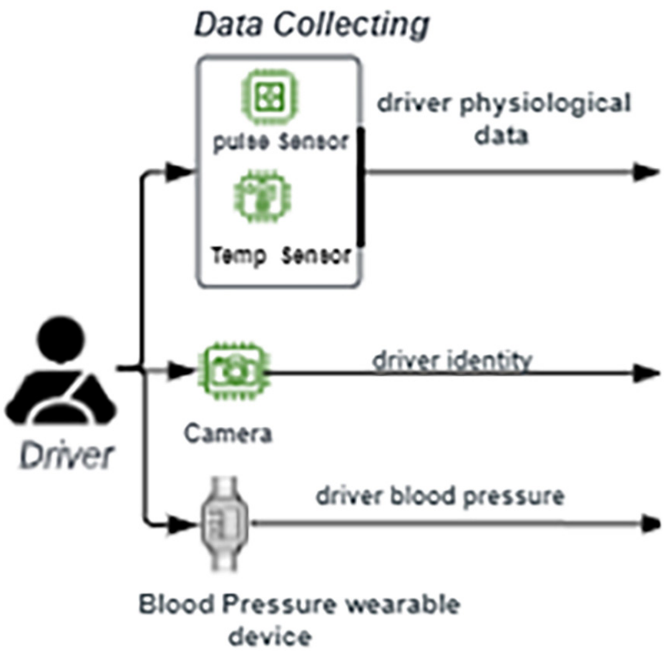

Fig. 2. Data collecting stage

In the initial stage of our system, a camera serves as an indicator that the process has commenced. The camera is essential for streaming visual images to identify the driver. Utilizing computer vision techniques, it can perform facial scans and efficiently track symptoms. The PiCam360, a 360-degree panoramic camera based on Raspberry Pi, significantly enhances real-time health monitoring by offering a broad field of view, making it ideal for continuous patient monitoring in both hospital and home settings. Additionally, it supports compatibility with rotation sensors and high-resolution real-time video streaming, enabling precise tracking of patient movements and vital signs, with capabilities reaching up to 4K HDR. Furthermore, its open-source hardware and software allow for easy customization and seamless integration with other health monitoring devices, thereby improving overall patient care and safety [24]. The PiCam360 used in this system is depicted in Figure 3.

Fig. 3. pi 360 camera [24]

The IoT is one of the most significant advancements made in recent technological times [25]. Researchers found that heart rate to be in the normal range (for most people of average age) of 60–100 beats per minute (bpm) [26]. Rate Beats at each time can give very important information about health conditions and is thus a very valuable parameter to monitor, especially for those who have heart problems and are at elevated risk [27]. To address this need, the MAX30100 pulse oximeters and heart rate sensors play a vital role in real-time monitoring. It utilizes two LEDs (red and infrared) and a photodetector to shine light onto the skin and measure the amount of light reflected, enabling accurate and continuous heart rate tracking, which varies with blood flow. By analyzing these variations, it calculates the heart rate in BPM and blood oxygen saturation (SpO2), Figure 4 shows the MAX30100 sensor [28].

Fig. 4. MAX30100 sensor [28]

This integration of IoT technology and advanced sensors exemplifies how modern innovations can enhance healthcare delivery and improve patient outcomes.

The average human body temperature is a crucial physiological indicator that offers significant insights into an individual's health. Recognizing the standard range of body temperature and how it is regulated can aid in detecting and addressing abnormal temperatures, which may signal an underlying health issue. For healthy adults, the typical body temperature is around 37°C, with variations influenced by factors such as age, gender, physical activity, and time of day. Flexible temperature sensors primarily rely on the alteration of electrical signals in heat-sensitive materials caused by temperature changes to enable real-time temperature monitoring [29].

Figure 5 displays temperature sensors, including MLX90614, a non-contact infrared temperature sensor designed for real-time temperature monitoring. It works by detecting the infrared radiation emitted by an object and utilizes a thermopile detector to absorb this infrared energy, converting it into an electrical signal. This signal is then processed to determine the object's temperature. The sensor is available in 3V and 5V operating voltage versions and can measure temperatures within a body temperature range of –70°C to 382.2°C and an ambient temperature range of –40°C to 125°C. It achieves an accuracy of 0.02°C when the object is positioned 2 cm to 5 cm away from the sensor [30].

Fig. 5. MLX90614 temperature sensor [30]

The ESP32 is a microcontroller board tailored for IoT applications, equipped with a robust dual-core Tensilica LX6 microprocessor capable of operating at speeds up to 240MHz. It includes 520KB of SRAM and 4MB of flash memory, along with integrated Wi-Fi and Bluetooth connectivity, making it a versatile platform for developing connected devices and applications [31]. Developed by Espressif, the ESP32 board series offers numerous advantages, such as affordability, energy efficiency, and support for low-power modes such as deep sleep to conserve energy. It also features Wi-Fi functionality and user-friendly programming. Figure 6 illustrates the ESP32 board. Fluctuations in normal blood pressure (BP) levels are among the most prevalent heart attack factors, but various wearable BP devices have emerged as promising solutions to address this issue [40].

Fig. 6. ESP32 board [31]

3.2 Data preprocessing filtering

The second stage involves data preprocessing and analysis. Figure 7 illustrates its components, including the dataset, NN algorithm, the microprocessor, and the data interconnections between them. Additionally, the figure highlights the steps required to trigger the warning system following the analysis of driver data.

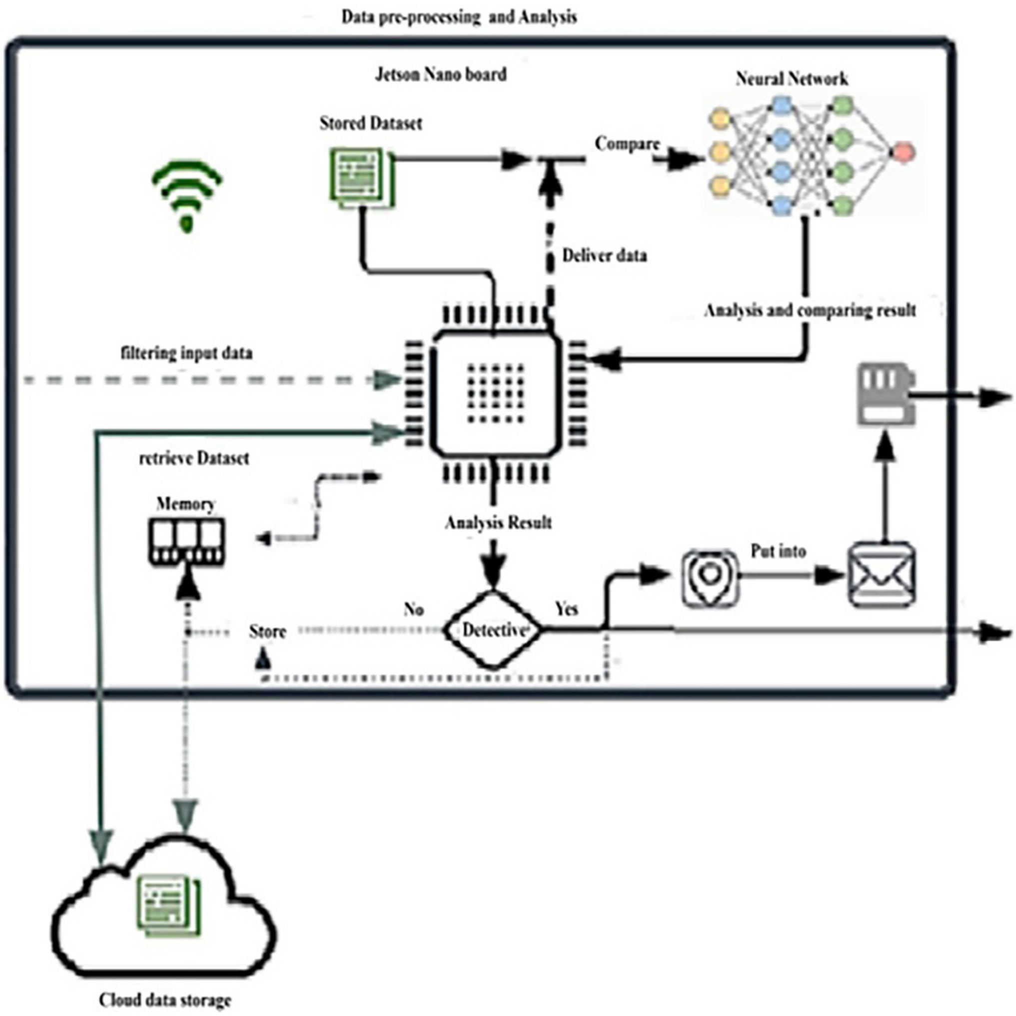

Fig. 7. Data pre-processing stage

Additionally, the system offers the flexibility to store the updatable dataset either in cloud storage or locally, with the capability to use an external backup memory that is pre-installed for emergency scenarios. To grasp how this stage functions, it is essential to first define its components, both hardware and software. The following section explains each component and its role in developing a system designed to detect and alert users of potential heart attacks.

Figure 8 shows the Nvidia Jetson Nano board. The usage of a camera aligns well with the system's requirements, and for this reason, the Nvidia Jetson Nano board was selected. This board is equipped with essential features necessary for building the system, including support for wireless connections, GPS and GSM sensors, sufficient memory, and a microprocessor, to run advanced AI workloads with a small size, low power, and low cost.

One of the challenges faced by the current system is to take into account external environmental factors that can affect the reliability of physiological symptom readings, for example, vehicle movements such as vibrations and sudden acceleration can lead to the introduction of noise in the sensor data, which puts the accuracy of vital symptom readings at risk. In addition to the effect of lighting differences inside and outside the car environment on the camera and sensors. Addressing these factors is extremely important to enhance the reliability of real-time heart attack detection systems, especially for safe and efficient deployment in dynamic driving conditions.

The moving Z-score algorithm is implemented in Python to address sensor noise or data anomalies [34]. It computes the Z-score for the most recent data points, flagging anomalies that surpass a defined threshold. This method is crucial for preserving data accuracy and enabling real-time detection of anomalies in dynamic data streams. The algorithm is detailed as Algorithm 1.

Algorithm 1: Moving Z-Score Algorithm

1. **Initialize Variables:**
    - **Create an empty list z_scores,anomalies**
2. **Iterate Through Data:**
    - **For each index (i) from 0 to the length of data minus 1:**
        - **Check Window Size:**
            - **If (i < window_size):**
        - **Append NaN to z_scores (not enough data to calculate Z-score).**
            - **Else:**
            - **Extract the moving window of the last window_size data points.**
            - **Calculate the mean and standard deviation of the moving window**
                - **Calculate Z-Score:**
        - **Append the calculated Z-score to z_scores.**
                - **Check for Anomalies**
3. **Return Results:**
    Return the lists z_scores and anomalies

3.3 Dataset

A dataset is a collection of data organized in a specific format, containing various types of information such as numerical and categorical data, as well as text and images in certain instances. Datasets can be structured in different forms, including spreadsheets or databases, and the data can be sourced from a wide variety of origins, such as experiments, surveys, or existing databases [35].

The data set of the system took into account the absence of the need for a set of symptoms associated with heart attacks, which are present in most of the six data, especially in dealing with heart attacks, such as cholesterol and whether he smokes or not, either because of the difficulty of measuring them or considering them not a physiological medical symptom that does not need to be present at the moment, as in Cleveland Heart Disease dataset (UCI Repository) and Framingham Heart Study dataset, this was replaced by adding the driver's medical history in order to ensure the accuracy of the results in the examination process, since those with a previous medical history are implicitly at risk.

The proposed system utilizes a custom-built dataset specifically designed for its purpose. This dataset includes critical known heart attack symptoms and introduces a new feature called "history" which captures the driver's medical history to enhance the accuracy of the results. The dataset comprises 12 columns and 1,467 rows. It may contain some redundancy, noise, and missing values, which will be addressed using specialized data processing techniques discussed in the subsequent stages of preprocessing. Each dataset may contain various types of anomalies, such as missing values, redundancy, or other issues. To address these problems, a preprocessing step is essential. This step involves three stages before the data is ready for analysis [36]:

- **Format:** The dataset used for the implementation may contain specific attributes whose names do not appear in (dataset name) and contain specific attributes that are irrelevant and not useful for the most unique performance proposed.
- **Cleanup:** This part of the preprocessing belongs to removing or repairing the missing entry in the data frame. This step is recommended for the row that contains these incomplete columns to be removed and also to remove some duplicate entries in the data frame.
- **Sampling:** This is also done on the dataset to improve the performance of the algorithm it, and this may cause the algorithm to take longer. During the testing phase, it is crucial to accurately represent the dataset to assess the system's actual operational performance. Sampling is not necessary during other phases of development, such as the training phase. However, certain situations may require greater representation due to their significance in learning the system's behavior or their difficulty level. Therefore, these situations may be more prevalent in the training phase. The data used for building this dataset is taken in real-time.

The proposed system measures heart rate and body temperature through sensors embedded in the car (steering wheel) and blood pressure by a wearable device put around the driver's arm. It is compared to pre-determined threshold values based on the following criteria:

- Fluctuations in heart rate: One of the most common signs of a heart attack is heart rate when it is faster or slower than normal by more than 100 BPM or less than 60 beats per minute [37].
- Fluctuations in Body Temperature: Abrupt temperature changes are common and recognized in heart attacks; the minimum average body temperature is 37 degrees Celsius [38].
- Fluctuations in oxygen levels in the blood: If the rate of oxygen in the blood is less than 90%, it is considered low and leads to a lack of oxygen in the blood, If the rate of oxygen in the blood is less than 80%, it may lead to the deterioration of the functions of organs such as the heart and its continued decline in heart attacks [39]. Through the pulse sensor, blood oxygen levels (SpO_2) can be obtained.
- Fluctuations in blood pressure (rise/fall): Blood pressure can sometimes drop before a heart attack due to a pain response. High blood pressure can accompany a heart attack caused by the surge of hormones, such as adrenaline that floods the body during stressful situations. Both systolic and diastolic hypertension contribute significantly to cardiovascular risk, American Heart Association BP guideline (BP-H ≥130 mm Hg or BP-L ≥80 mm Hg) [40].
- The previous medical history of the driver is closely related to the recurrence of these symptoms. Through the camera, the driver can be recognized.

After conducting the recognition scan, the previously stored data can be accessed directly, the comparison process can be performed, and the entered data can be checked faster. Based on the data set of this proposed system, the appropriate steps were taken. Table 1 shows a system heart attack dataset description.

Table 1. Dataset descriptions

Attribute	Data Type	Description
ID	Number	Person number
Age	Number	Years
Gender	Binary	1: male, 0: female
T	Number	Body Temperature
P	Number	Heart Rate (Pulse)
BP-H	Number	Higher Blood pressure
BP-L	Number	Lower blood pressure
SpO2	Number	Oxygen level in blood
History	Number	1: have a heart attack before 0: don't have a heart attack before
Result	Char	Positive: Risk area of Heart Attack Negative: Not in Risk area of Heart Attack

Evaluation metrics. Machine learning model evaluation is accomplished by using test and score equations to assess performance. These equations offer metrics such as accuracy, precision, recall, and overall performance that are used to gauge the effectiveness of the model [41]. Test equations are used to evaluate the machine learning model's performance on a portion of the dataset that wasn't used during training to measure the model's ability to generalize to new and unseen data. Score equations evaluate the model's performance on the training set, providing insights on how the model performs on the data it was trained on, and can identify areas for improvement. Different metrics such as accuracy, precision, recall, F1 score, confusion matrix, and ROC curve can be utilized in evaluating the model's performance [42].

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

$$\text{Precision} = TP/(TP + FP)$$

$$\text{F1 Score} = 2*(\text{Precision}*\text{Recall})/(\text{Precision}*\text{Recall})$$

$$\text{Recall} = TP/(TP + FN)$$

In binary classification, a model predicts whether a sample belongs to one of two possible classes. the four negative class possible outcomes for a binary classification model are [43]:

- **True positive (TP):** The model correctly predicts the positive class.
- **False positive (FP):** The model incorrectly predicts the positive class.
- **True negative (TN):** The model correctly predicts the negative class.
- **False negative (FN):** The model incorrectly predicts the negative.

To validate the accuracy of the results, two methods were employed to demonstrate the effectiveness of the NN algorithm. First, the orange tool was used as a preliminary experiment to compare the NN algorithm with other machine learning algorithms, such as support vector machines (SVM), random forest, and logistic regression. This tool was chosen because it offers data visualization capabilities and supports a wide range of machine learning algorithms, ensuring flexibility for various analytical needs. Subsequently, the Visual Studio simulator was utilized to obtain the results and assess the reliability of the system.

The proposed system was developed using Visual Studio Code, operating on a computer equipped with an Intel® Core™ i7 processor and 8.00GB of RAM. The system ran on a Windows 10 64-bit operating system. The hardware and software specifications used for experimenting are detailed in Table 2.

Table 2. Machine configuration used to run the experiments

Configuration	Specification	
Hardware	CPU	Intel® Core™ i7
	RAM	8GB RAM
Software	Operating System	Windows 10 64-bit
	Dataset	Research dataset
	Simulator	Visual Studio Code

4 WARNING SYSTEM

This study introduces a warning system aimed at offering prompt assistance when a driver experiences a heart attack while on the road. The proposed system utilizes advanced technology to facilitate seamless communication with the driver, their family members, and emergency response teams via messages and notifications. This ensures a swift and well-coordinated emergency reaction during crucial situations.

The warning system relies on smart devices, such as smartphones, which utilize various communication networks to effortlessly provide the driver's geographical location, which has become more widely available in the current situation. In the event of a malfunction in the communication network used by these devices, text messages are automatically sent via the service provider's corporate chip installed within the vehicle.

The warning system is triggered based on the outcome of the NN analysis of the driver's vital signs. A positive result indicates that the driver is in a heart attack risk zone. The activation process involves the following steps:

1. **Driver alert:** If a critical condition is detected, the system sends a warning notification and an SMS message with the examination results to the driver's phone.
2. **Immediate family notification:** As soon as heart attack risk zones are identified, the system automatically sends a distress SMS to the driver's pre-selected family members or emergency contacts. This message includes crucial details such as the vehicle's location and an emergency text.
3. **Rescue team activation:** While notifying the family, the system begins communicating with nearby rescue teams or emergency services. It transmits essential information to enable a swift response to the emergency.

The main benefits of the proposed warning system:

1. Quick response: Notifications ensure direct communication with rescue teams and help to reach the driver immediately, saving precious minutes in an emergency.

2. Family communication: The proposed system keeps family members informed and engaged during emergencies, enhancing a sense of security and reassurance even from a distance.
3. Reduce road accidents: Providing early warnings for drivers suffering from heart attacks reduces the risk of accidents caused by sudden heart attacks.
4. Easy integration: The warning system is integrated into existing vehicle systems, making it accessible to many drivers.

5 RESULT

The performance results presented in the analysis process show that the proposed system is highly effective in using NNs to identify areas of risk for heart attacks among drivers. The NN algorithm proved to be the most accurate in detecting heart attack risk among other machine learning algorithms, this was tested on a dataset specially designed for the proposed system.

5.1 Dataset features and pre-processing

Following an interview with a cardiologist consultant and a review of relevant scientific research and datasets from specialized websites, the dataset was meticulously designed to align with the experimental requirements of the proposed system. The dataset size was optimized by selecting the most critical features for identifying heart attack risk areas, while potentially excluding less relevant ones. Key features such as pulse rate, blood oxygen levels, body temperature, and blood pressure were chosen due to their ease of accurate measurement and minimal susceptibility to environmental influences, unlike other factors such as ECG data, which can be significantly affected by the driver's surroundings. Additionally, the dataset incorporated a novel feature: the driver's medical history. This feature leverages the system's built-in camera to recognize the driver and assess their predisposition to a heart attack in advance.

The dataset for the proposed system comprises 12 columns and 1,467 rows. The results are labeled as (Positive) if the driver is identified as being in the heart attack risk zone and (Negative) if they are not. To ensure data reliability and achieve optimal performance, essential data preprocessing steps were carried out. These procedures are crucial for improving the system's accuracy and its ability to effectively manage real-world datasets. One of the preprocessing tools used, Orange, includes a function to discretize continuous variables. This function converts numeric attributes into categorical ones, employing an equal frequency method to divide the attribute into a specified number of intervals, each containing approximately the same number of instances. In the Python implementation, the dataset was split into 80% for training and 20% for validation, with 100 iterations and a batch size of 25.

5.2 Neural network performance and flexibility

One of the key strengths of the proposed system lies in its application of an NN algorithm to tackle the intricate challenge of identifying heart attack risk areas, particularly in light of synchronous and time-dependent developments. The NN's capacity to discern complex patterns and relationships within data has demonstrated its effectiveness in delivering highly accurate outcomes. To evaluate the system's capability in pinpointing heart attack risk areas, an experiment was carried out using the orange tool software, comparing the NN algorithm with various other machine learning algorithms, as illustrated in Table 3.

As illustrated in Table 3, the proposed system achieved precision, F1 score, and recall values of (0.970, 0.970, 0.970), outperforming all other machine learning models in comparison. The confusion matrix reveals that the true/false and false/true cases accounted for only 8 out of 294 samples, indicating a negligible impact on the overall results. Figure 8 displays the confusion matrix of these outcomes. The system was tested independently, without integration with a car, using random samples to evaluate the functionality and reliability of its approach and components.

5.3 Result discussion and comparison

In this study, we propose a system designed to detect heart attack risk areas and provide emergency alerts if such a risk is identified for vehicle drivers. The system integrates general-purpose machine learning algorithms with data from various sources, including pulse sensors, temperature sensors, camera inputs, and wearable blood pressure devices, to create a smart detection system. This system can determine whether drivers are in heart attack risk area. Our approach stands out by simultaneously utilizing data from an in-vehicle camera, sensors embedded in the steering wheel, and a wearable device on the driver's arm, which is then processed and evaluated by precise classifiers. To ensure data quality during the preprocessing stage, several functions are employed, including a continuous variable estimation function, which enhances data reliability and converts numerical attributes into categorical ones.

To accomplish the study's objective, a dataset was specifically designed for the proposed system, consisting of 12 columns and 1,467 rows, to assess the system's performance. The dataset was developed following an interview with a consultant cardiologist and a review of scientific research that included relevant datasets. This process helped in selecting the key features necessary for identifying heart attack risk areas.

The dataset was constructed following an interview with a consultant cardiologist and an analysis of scientific research that included relevant datasets, aiming to identify features capable of detecting heart attack risk areas and gathering real-world data. Investigating the interpretability of the NN can provide valuable insights into the model's decision-making process, fostering greater trust in its detection capabilities. This study highlights significant findings regarding the successful implementation of an NN-based system for identifying heart attack risk areas in drivers.

The integration of various devices, including a camera (pi360), a pulse sensor (MAX30100), a temperature sensor (MLX90614), a wearable blood pressure monitor, an ESP32 board, and a Jetson Nano board, enabled the collection and processing of physiological signals using custom software such as Visual Studio Simulator and an NN algorithm. This approach facilitated the creation of a tailored dataset and its subsequent analysis, yielding highly accurate results that underscore the scientific significance and practical potential of the system. This study marks a significant step forward in enhancing road safety measures and medical interventions, paving the way for further advancements in predictive medical technologies.

The evaluation process demonstrated the superiority of the NN algorithm over other machine learning algorithms, achieving an accuracy of 97% in analyzing the dataset specifically designed for this proposed system. When comparing our work with previous studies, several methods for identifying heart attack risk areas emerge.

For instance, Hannun et al. (2019) developed a model that trained NN algorithms to detect cardiac arrhythmias, including those linked to heart attacks, achieving an accuracy of approximately 94.4%.

Mahendiran et al. (2023) introduced a model utilizing NNs to predict heart attacks based on cardiovascular data, achieving an accuracy of approximately 82%. Similarly, Sajja & Kalluri (2020) proposed a CNN for early-stage prediction of cardiovascular disease, attaining an accuracy of 94%. Additionally, Ali et al. (2019) developed an expert system employing two SVM to efficiently predict heart disease, with an accuracy of 92.22%. Table 3 show's comparing result for this model with other related models that focus on the heart attack detecting process.

Table 3. Related models comparisons

Citation	Algorithm Used	Accuracy Achieved
Hannun et al. (2019)	NN	94.4%
Mahendiran et al. (2023)	NN	82%
Sajja & Kalluri (2020)	CNN	94%
Ali et al. (2019)	SVM	92.22%

In order to enhance the credibility of the reported performance, we conducted statistical validation in addition to standard metrics. The test set reached 20% of the model dataset. Our model achieved an accuracy of 97.0%, a precision achieved 0.9905, a recall achieved 0.9375, and finally an F1 score achieved 0.9634. We computed 95% confidence intervals (CI) using the Wilson score method [47]:

Precision: 0.9905 (95% CI: [0.945, 0.999])
Recall: 0.9375 (95% CI: [0.877, 0.970])
F1 Score: 0.9634 (95% CI: [0.930, 0.980])

Additionally, we evaluated the statistical significance of performance differences by using McNemar's test [48], comparing our model to Hannun et al. (2019), who achieved 94.4% accuracy. By the confusion matrix in Figure 8 we obtained a McNemar's $\chi^2 = 4.00$ with $p = 0.0455$, that indicates the proposed model at the 0.05 level give improvement is statistically significant.

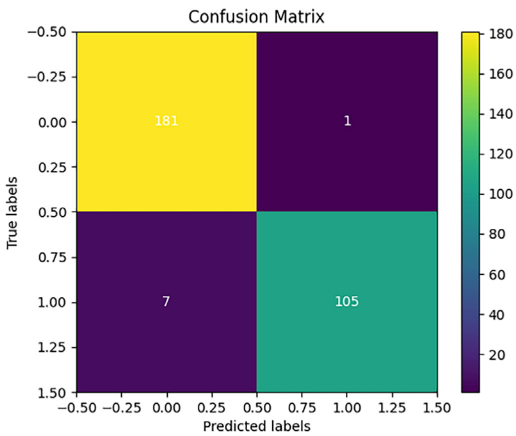

Fig. 8. Confusion matrix

In opposite, models by Mahendiran et al. (2023), Sajja and Kalluri (2020), and Ali et al. (2019) reported lower accuracies (82%, 94%, and 92.22%, respectively), with no published significance testing or confidence intervals. Our results not only exceed these standards but also demonstrate statistically validated superiority, reinforcing the Effectiveness of our model.

6 CONCLUSION AND FUTURE WORKS

This study introduced a real-time, low-cost health monitoring system that uses wearable devices and in-car sensors to detect early signs of heart attacks in drivers. By integrating heart rate and temperature sensors, a camera, and an NN-based analysis unit on a microcontroller, the system achieved a high detection accuracy of 99.2%. These findings support the system's potential to reduce road accidents caused by medical emergencies and to enhance driver safety through proactive health monitoring.

Future work will focus on deploying the system in actual vehicles to evaluate its performance under real-world driving conditions, including variables such as road vibration, ambient temperature, and user behavior. Hardware integration with vehicle systems (e.g., onboard diagnostics and in-vehicle infotainment units) is also planned to facilitate ideal alerts and emergency communication; furthermore, a field test will be conducted to verify the robustness of the system across demographics. Expansion of the dataset and comparison with other ML/DL models (e.g., CNNs for facial or behavioral analysis) will be explored to enhance diagnostic reliability and reduce false warnings. This study depends on the acceptance of car companies to apply it in reality and add it among the smart systems included during manufacturing so that it is part of the features of the vehicle itself, with its ability to assist in protecting lives.

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