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Research Article

IoT-Driven Vehicle Management: Fully Elman Neural Network with Red Piranha Optimization-Based Drowsiness and Alcohol Consumption Detection in Smart Cities

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ABSTRACT

Recent research has focused on supporting drivers, revealing that the primary causes of road accidents are driver drowsiness and alcohol consumption. Thus, Drowsiness and alcohol consumption detection (DACD) are critical for IoT-based smart cities as they improve public safety by detecting and preventing incidents related to sleep and alcohol consumption. In this manuscript, an AI-enabled DACD using Fully Elman Neural Network (FENN) with Red Piranha Optimization (RPO) is proposed for Internet of Things (IoT) based smart cities. Initially, the IoT kit consists of several normal cars, ambulance cars, and roadside devices. The roadside devices which are transceivers fixed at predetermined locations, relay information to both normal and ambulance car devices. The system is designed to detect alcohol consumption, and driver drowsiness using data for each vehicle in the initial setup. The data collected by the IoT kit is preprocessed using the MaxAbsScaler Normalization approach. After that the deep learning model, specifically using FENN is applied in the preprocessed data to validate the detection results. Also, Red Piranha Optimization (RPO) is proposed for enhancing the weight parameters of FENN. By then the performance of the proposed FENN-RPO-DACD method is evaluated using the MATLAB platform, and the the performance evaluation is analysed using calculations like accuracy, False Positive Rate (FPR), Sensitivity, False Negative Rate (FNR), Precision, Recall, F-1 Score, Specificity, computational time. Thus, the proposed FENN-RPO-DACD method has achieved 18.98%, 21.56%, and 24.96% higher accuracy, 12.39%, 19.56%, and 29.67% lower Computation Time, 28.78%, 34.09%, and 38.67% lower FPR, 14.98%, 18.67%, and 21.09% higher sensitivity, 18.97%, 21.56%, and 24.38% higher precision than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

Keywords: Internet of Things, Drowsiness, Smart Cities, Alcohol Consumption, Transceivers, Roadside Devices, Artificial Intelligence, Public Safety, Red Piranha Optimization, Fully Elman Neural Network.

INTRODUCTION

As urban populations grow and the complexity of transportation systems increases, the need for improved road safety becomes more pressing [1]. Smart cities are turning to the Internet of Things (IoT) to address these challenges, enabling connected devices and advanced data analytics are used including managing traffic and road safety [2]. Vehicle management, particularly detecting driver drowsiness and alcohol consumption [3], is one important area where the Internet of Things (IoT) will have a significant impact. By coordinating sensors, side-of-the-road gadgets, and unified information handling units, IoT-empowered frameworks can screen and dissect driving ways of behaving, add to more secure streets, and lessen the gamble of mishaps brought about by hindered driving [4]. Drowsiness and liquor utilization are two main considerations adding to street mishaps overall [5]. Customary location techniques, for example, side-of-the-road tests and driver self-evaluations, are lacking in forestalling mishaps before they happen [6]. However, drivers can now continuously monitor their physical and mental states while driving thanks to IoT technology [7]. In-vehicle sensors, for example, cameras and breathalyzers can catch continuous information on looks, eye developments, and liquor levels [8]. In the meantime, environmental sensor-equipped roadside devices can monitor vehicle speed, road conditions, and other external factors [9]. This abundance of data enables more accurate and timely detection of potential dangers by providing comprehensive images of the driver's position and the environment around him or her [10]. As well as working on quick security, IoT-driven vehicles the executive's frameworks can change how urban communities address long-haul transportation challenges [11]. By aggregating large amounts of data from numerous vehicles and roadside devices, cities can gain deep insights into traffic patterns, high-risk areas, and the root causes of crashes [12]. The placement of traffic signals, the design of roads, and speed limit enforcement will all benefit from improved infrastructure planning tailored to the particular requirements of various urban areas thanks to this data [13].

Besides, these frameworks are coordinated with other smart city advancements, like shrewd traffic the board and independent vehicles, to shape an incorporated, interconnected metropolitan environment where every component adds to general security and productivity [14]. At last, as these IoT-driven frameworks become more far and wide, they will prod progresses in related advancements, for example, computerized reasoning and AI [15]. The constant flow of information from vehicles and roadside devices gives a priceless asset to refining strategies to recognize drowsiness, alcohol consumption, and different types of driving [16]. This consistent criticism circle of information and improvement will prompt always refined identification techniques equipped for recognizing unobtrusive marks of weakness past the compass of existing advances [17]. As these frameworks develop, they won't just further develop security on streets but additionally drive advancement in numerous areas and add to the more extensive progression of smart city drives. In this IoT-driven vehicle the executives' framework, the gathered information is shipped off a concentrated information handling unit and dissected utilizing progressed calculations, including deep learning models [18]. These calculations are intended to recognize designs that show languor or alcohol consumption, considering mediations to forestall mishaps [19]. Assuming a perilous way of behaving is distinguished, the framework can give admonitions to the driver, change the vehicle's speed, or ready crisis administrations. As smart urban communities keep on developing, the joining of IoT into the vehicle of the executive's frameworks is a significant stage toward establishing more secure and more proficient metropolitan conditions [20].

Manuscript Novelty

The novelty of the manuscript is explained as follows,

- The system uses IoT technology to create a connected network of ordinary cars, ambulance cars, and roadside devices, enabling real-time communication and data sharing to improve road safety.
- Pre-processing the data using the MaxAbsScaler normalization technique ensures that the data is properly scaled and improves the overall performance of the deep learning model.
- FENN's application is innovative in its ability to effectively capture and analyze temporal patterns in data to detect drivers' sleepiness and alcohol consumption accurately.
- The introduction of RPO as an optimization technique to fine-tune the weight parameters of FENN is a novel approach that improves the accuracy and performance of the detection system.
- The system not only detects drowsiness and alcohol consumption but also integrates warning mechanisms, making it a robust solution for improving road safety in smart city environments.

Manuscript Contribution

The contribution of the manuscript is explained as follows,

- Initially, the IoT kit consists of several normal cars, ambulance cars, and roadside devices. The roadside devices which are transceivers fixed at predetermined locations, relay information to both normal and ambulance car devices.
- The data collected by the IoT kit is preprocessed using the MaxAbsScaler Normalization approach.
- After that the deep learning model, specifically using Fully Elman Neural Network (FENN) is applied in the preprocessed data to detect alcohol consumption, and driver drowsiness.
- Also, Red Piranha Optimization (RPO) is proposed for enhancing the weight parameters of FENN.

The remaining sections of the manuscript are organized as follows: Section 2 presents the related work, Section 3 describes the proposed method, Section 4 highlights the results and analysis, and Section 5 provides the conclusion.

RELATED WORKS

This section contains recent attempts among numerous studies on detecting alcohol consumption, and driver drowsiness in vehicles using a DL approach.

In 2022, Abu Al-Haija, Q. and Krichen, M [21] have presented six MQ-3 alcohol sensors in an in-vehicle detection system, processing the data with an optimized shallow neural network (O-SNN). The system achieves better detection accuracy with a minimum inference delay, making it ideal for real-time applications in the Driver Alcohol Detection and Safety System (DADSS). The system's high performance and low latency support widespread deployment to prevent drunk driving. However, reliance on MQ-3 sensors may be a limitation as they sensitive to other materials and may not address other types of impairment.

In 2024, Jagatheesaperumal, S.K.,*et.al.*, [22] have presented AI-IoT technologies for smart city road safety, using sensors such as eye blink, ultrasonic and alcohol detectors to monitor driver behavior and vehicle environment. The system provides real-time alerts, adjusts vehicle speed, and notifies authorities when required. A key advantage was its comprehensive approach, improving safety and connectivity through Li-Fi-based inter-vehicle communication. However, potential limitations include sensor accuracy and the need for widespread infrastructure upgrades to support Li-Fi and AIoT integration in urban areas.

In 2022, Minhas, A.A *et.al.,* [23] have presented a real-time driver sleep detection method using Convolutional Neural Networks (CNN), specifically evaluating models such as InceptionV3, VGG16 and ResNet50. Among these, ResNet50 achieved the highest accuracy, making it highly effective in sleep detection. The method uses a custom dataset containing side and front views of drivers to improve real-time performance. The main advantage was the high accuracy and relevance of the dataset to real-world driving scenarios. However, there was limitation in the need for extensive data and computational resources for effective sequencing at large scale.

In 2021, Sabri, Y.,*et.al.,* [24] have presented an IoT-based system aimed at preventing road accidents by addressing key causes of crashes and integrating post-crash measures. The system was designed to detect potential hazards, avoid accidents, and take immediate action when necessary, thereby enhancing vehicle safety, security, and efficiency. The advantage lay in its proactive approach to saving lives by preventing accidents and managing post-crash scenarios. However, the system's effectiveness was potentially limited by the need for widespread IoT infrastructure and challenges in integrating various devices and sensors across different vehicles and environments.

In 2022, Fantin Irudaya Raj, E. and Appadurai, M [25] have presented IoT-based smart transportation systems, focusing on vehicle-to-vehicle and vehicle-to-infrastructure communication, which were fundamental to autonomous vehicles. It also explored an IoT-based smart parking system for smart cities. These technologies aim to improve road safety, traffic management, and parking efficiency. The advantage lies in their potential to enhance urban mobility and reduce congestion. However, limitations include the need for robust infrastructure, significant investment, and addressing privacy concerns associated with extensive data collection and communication between vehicles and infrastructure.

In 2024, Doniec, R.J.,*et.al.,* [26] have investigated the use of electrooculographic (EOG) signal analysis to detect alcohol intoxication using smart glasses to collect data from nine participants in a driving simulator. Simulated alcohol levels were applied using drinking glasses at various concentrations. Machine learning algorithms analyzed the data, including decision trees and bundle trees, with bundled trees achieving the highest accuracy. It used blink rate and saccadic velocity as key features for detection. The advantage lies in the ability to automate the detection of alcohol intoxication using non-intrusive smart glasses. However, the limitation was that the model relied on simulated addiction rather than real-world conditions, which may affect the generalizability of the results.

In 2023, ABBOOD, Z. and Yonan, J.F.,[27] have presented a Drowsiness Detection model to improve road safety by monitoring driver fatigue using eye and mouth movements. For accurate sleep detection, the system used a high-resolution camera and a deep cascaded CNN. Facial features were analyzed using landmarks from the Dlib toolkit, and the "eye aspect ratio" metric was used to quantify fatigue. Its high accuracy in detecting sleep was an advantage, while the limitation was reliance on optimal lighting conditions, which could affect performance in various real-world environments.

Problem Statement

The quick improvement of smart urban communities has required the improvement of cutting-edge vehicle executive frameworks to guarantee street well-being and effective traffic on the board. A significant issue is the discovery of sluggish driving and alcohol consumption, the two of which are huge supporters of street mishaps. Customary techniques for checking driver sharpness and collectedness frequently require nosy sensors or are restricted in their ongoing application, prompting lacking preventive measures. The combination of the Internet of Things (IoT) with deep learning offers a promising arrangement through ongoing, non-nosy observing of drivers' physical and conduct states through in-vehicle sensors and outer cameras. This approach works on the precision of identifying sleepiness and alcohol hindrance, accordingly lessening mishap rates and further developing generally speaking street wellbeing in smart urban communities. The test lies in making a dependable, versatile, and financially savvy framework that can flawlessly coordinate into the current foundation of smart urban communities while guaranteeing security and negligible disturbance to drivers.

PROPOSED METHODOLOGY

In this manuscript, an AI-enabled Drowsiness and Alcohol Consumption detection (DACD) using Fully Elman Neural Network with Red Piranha Optimization is proposed for IoT based smart cities. Initially, the IoT kit consists of several normal cars, ambulance cars, and roadside devices. The roadside devices which are transceivers fixed at predetermined locations, relay information to both normal and ambulance car devices.

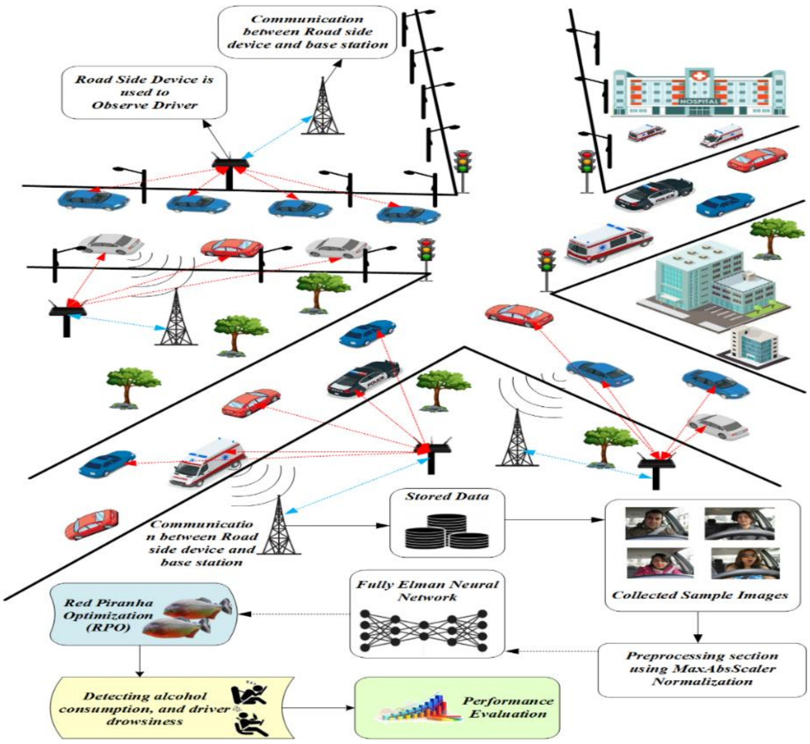

Figure 1: Block Representation of the Proposed FENN-RPO-DACD Methodology

The system is designed to detect alcohol consumption, and driver drowsiness using data from [28] and [29] for each vehicle in the initial setup. The data collected by the IoT kit is preprocessed using the MaxAbsScaler Normalization approach [30]. After that the deep learning model, specifically using Fully Elman Neural Network (FENN) [31] is applied in the preprocessed data to validate the detection results. Also, Red Piranha Optimization (RPO) is proposed for enhancing the weight parameters of FENN [32]. Figure 1 displays the suggested methodology's block diagram, followed by a full discussion of the proposed framework.

System Model

In smart cities, the integration of the IoT is revolutionizing road safety, particularly in the detection of driver drowsiness and alcohol consumption. The proposed system consists of in-vehicle sensors, roadside devices, and a centralized data processing unit**.** The in-vehicle sensors include cameras that capture the driver's facial features and eye movements, as well as breath analyzers that periodically measure alcohol levels. The system model is represented in figure 2.

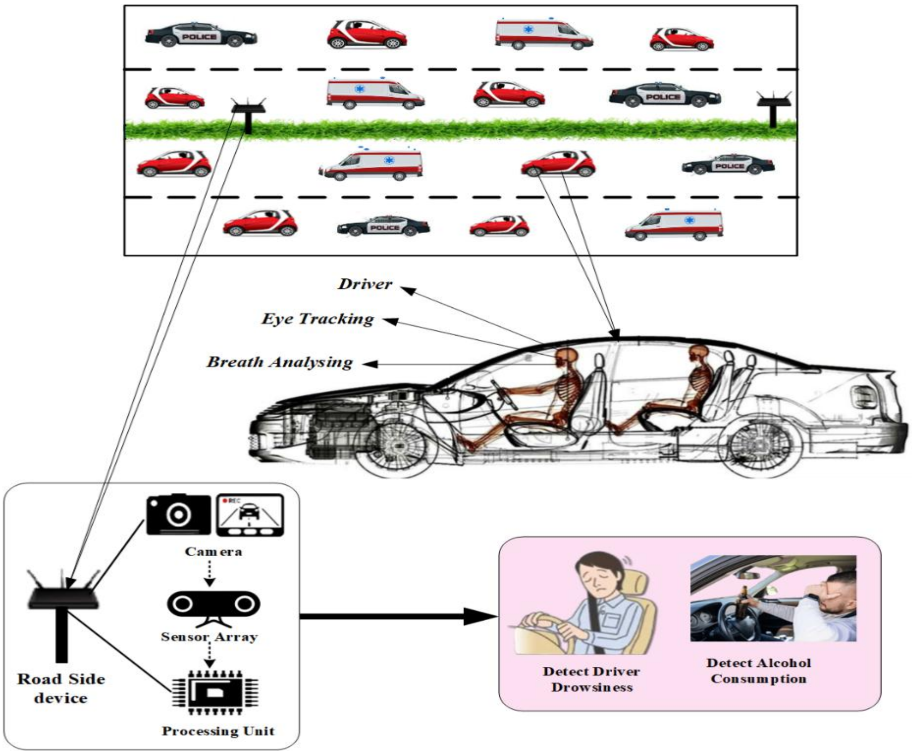

Figure 2: System Model

Roadside devices equipped with sensors and data collectors are strategically placed along the driving route to monitor vehicle speed, lane positioning, and road conditions.

Components of Ambulance Car Device

The road ambulance car device acts as a transceiver system encompassing various elements such as an Arduino Uno, a DC motor, a motor driver, an LCD, hard keys, and IoT connectivity. This receives the time-sensitive information forwarded by road conditions and facilities in terms of its availability, which is further displayed on the LCD. After processing this information, it sends a notification to the corresponding road device for smooth navigation and communication of the ambulance car.

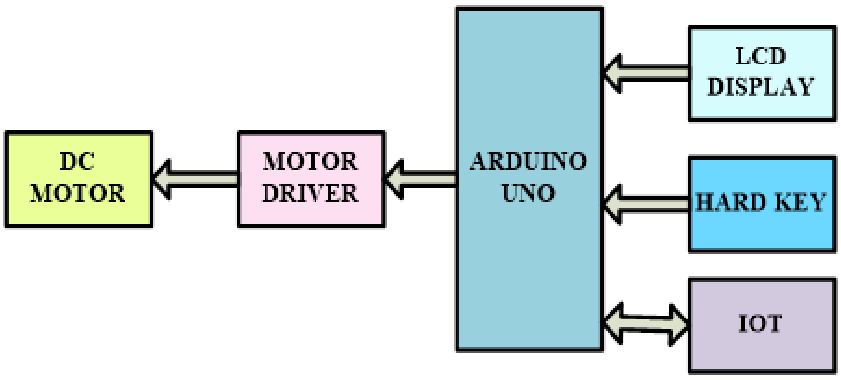

Figure 3: Components of Ambulance Car Device

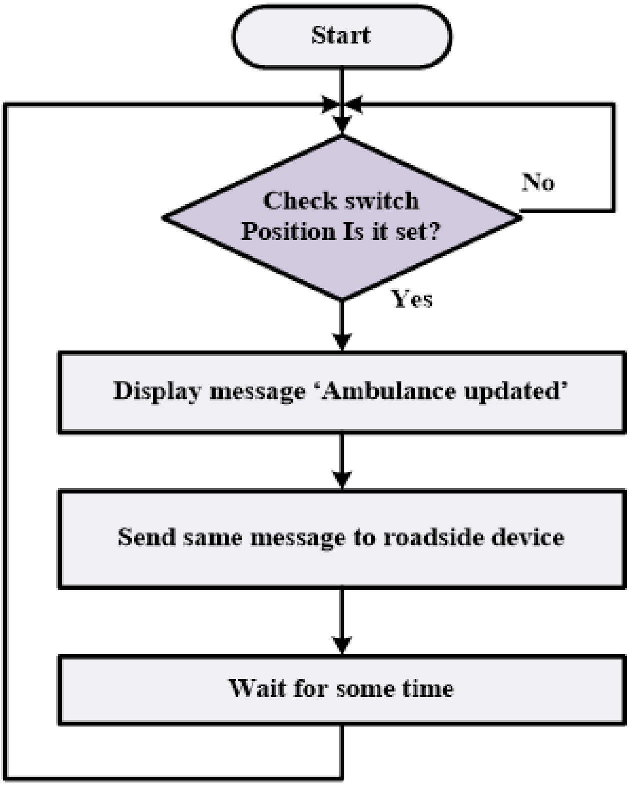

Figure 4: Flow Chart for Ambulance Car Device

Figures 3 and 4 are shown, describing the apparatus structure and flow of work within the operation, describing the role of the device in reducing time to response while increasing safety in an ambulance.

Components of Normal Car Device

The normal car device, in this case, included the following essential components: Arduino Uno, a DC motor, a motor driver, an LCD, an alcohol sensor, an IoT connection, and even an eye-blinking detection system. This was placed inside the car, served as a receiver, and acquired all the information through the IoT from the road device.

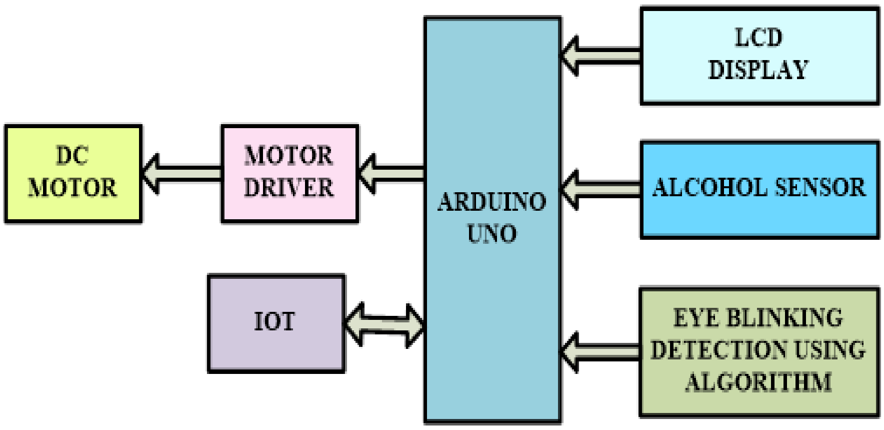

Figure 5: Components of Normal Car Device

The data received contains information such as the speed limit of the road, whether the driver's level of alcohol was detected, the driver's level of drowsiness through an eye-blinking detection algorithm, and the ID of the road. Other data is received including the word "ambulance" and a notification of the proximity of an ambulance for notification to the driver of its presence. Figures 5 and 6 depict the constituents of the gadget and its working flow respectively so that maximum safety on the road and the vigil for the driver are ensured.

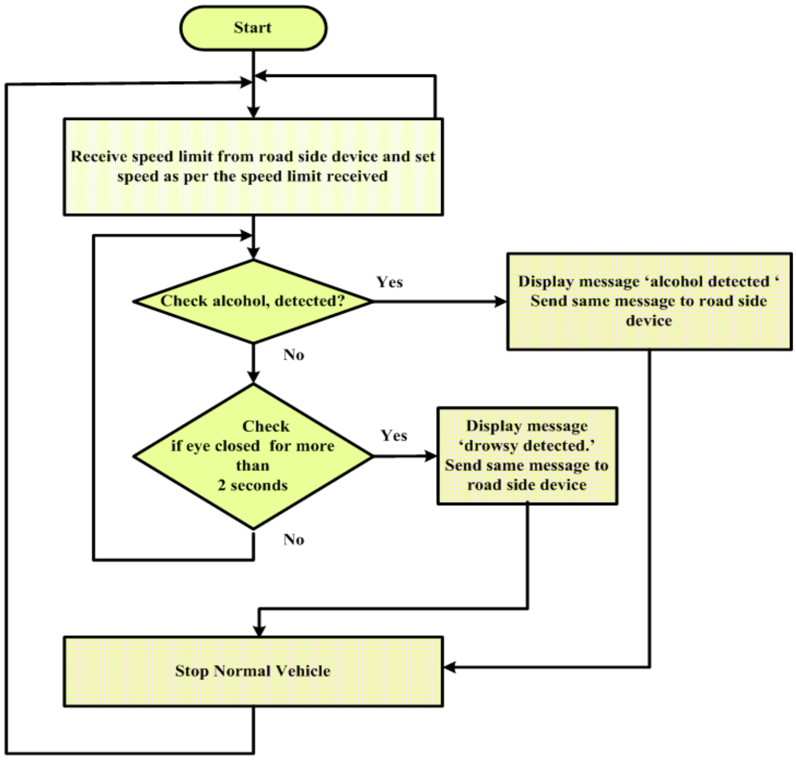

Figure 6: Flow Chart for Normal Car Device

Components of Road Side Device

The roadside device, which acts as a transceiver, is installed at predetermined places on the road. It gathers substantial information about the legal speed limit, facilities of the road, and the ID of the road itself, from a GUI provided on a PC. The device then communicates the road information and the speed to both normal car devices and ambulance car devices. This system is designed to work at speed limits between 0-150 km/h. Figure 7 Displays the roadside device components of this system. These are responsible for collecting very accurate road data which the vehicles in use take forward for safe and efficient driving.

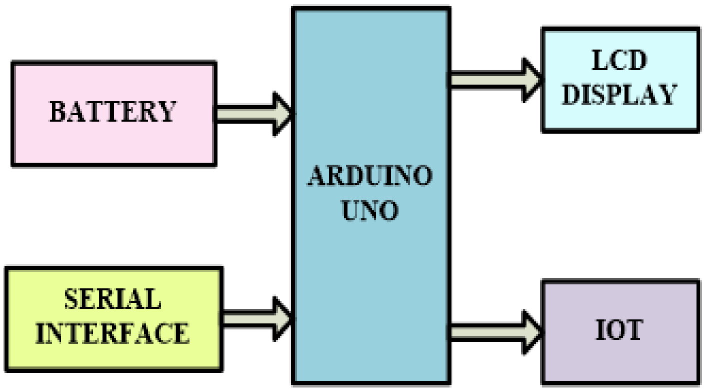

Figure 7: Components of Road Side Device

The PC, while booting up, sends critical road information, like the permissible speed limit, the road ID, and available facilities (hospital, school, crossing, factory, market, car park, and crossroads), to each roadside device one by one. The data is different for every road. The roadside device, based on that, broadcasts this information to all the vehicles present on that specific road. There are two possible scenarios for the transfer of information between a road device and car devices as follows:

Normal Car: The roadside device receives data from the PC and conveys the same to all normal cars on that road. The information availed is on legal speed limits and other details concerning roads.

Ambulance Car: Once an ambulance enters a particular road, it sends a message to the road device and informs the latter of the availability of the ambulance. The road device will then inform all vehicles moving along that road about the ambulance's presence. Moreover, the road device will inform any facilities present along the road like the hospitals to the ambulance car for effective route management. Figure 7 represent the components of roadside device and Figure 8 represents the flow chart of roadside device operation.

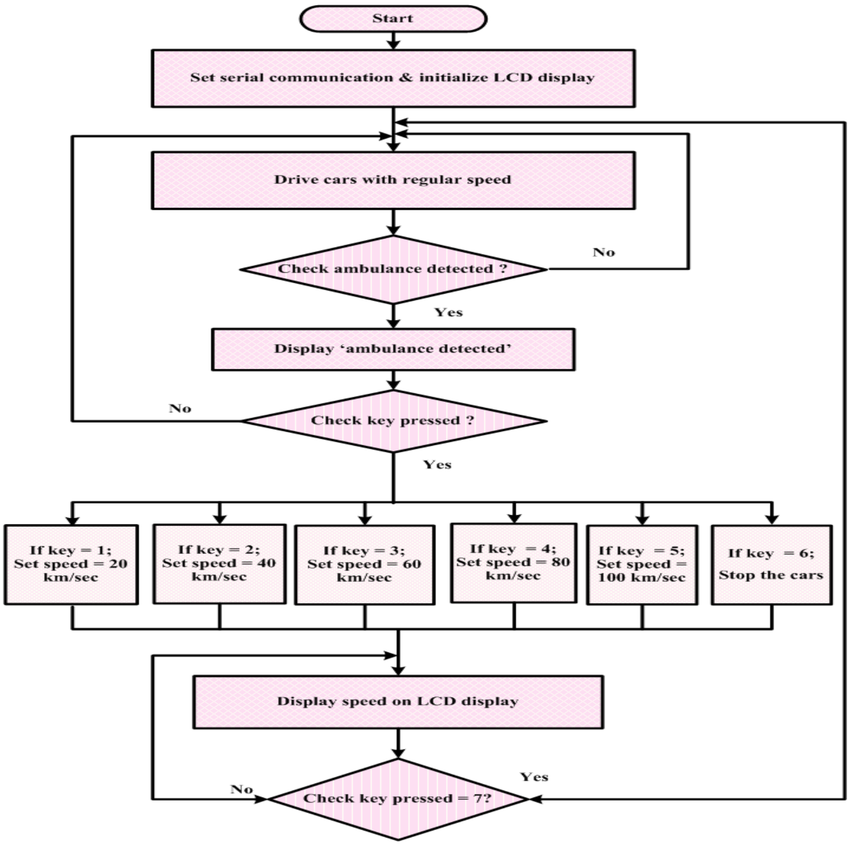

Figure 8: Flow Chart for Road Side Device

The road side devices communicate with the centralized data processing unit, where all collected data is stored for analysis. The stored data [28] and [29] is used for further analysis like detecting drowsiness or alcohol consumption. Here, the proposed deep learning algorithm is applied to this aggregated data to detect patterns indicative of drowsiness or alcohol consumption.

MaxAbsScaler Normalization

The collected data is preprocessed using a MaxAbsScaler-based normalization model that cleans the data by addressing missing values, outliers, and noise. Unlike previous scalers, MaxAbsScaler maps absolute values to the range [0, 1]. This scalar does not shift or center the data, and preserves the sparsity of the input data. The formula used in MaxAbsScaler for scaling each feature y_i of a data Y is denoted in equation (1),

$$y'_i = \frac{y_i}{Max(Abs(Y))} \tag{1}$$

Where, y'_i denotes the scaled value of feature y_i, and $Max(Abs(Y))$ is denotes the maximum absolute value of all features for all data samples in the dataset.

Fully Elman Neural Network (FENN) For Detecting Drowsiness and Alcohol Consumption

In this section, FENN is used to detect sleep and alcohol consumption. FENN is a type of Recurrent Neural Network (RNN) designed to effectively detect sleepiness and alcohol consumption in drivers by analyzing temporal patterns in the data. Unlike traditional neural networks, FENN includes recurrent connections that allow it to maintain the memory of previous inputs, making it well-suited for processing continuous data, such as time-series signals from sensors that monitor a driver's physiological and behavioral states. For sleep detection, FENN can analyze features such as eye-closure duration, blink rate, and head movements, while for alcohol consumption, it can process data from breath sensors or other indicators of impairment. By continuously learning and adapting driver behavior over time, FENN can provide accurate, real-time alerts to prevent accidents.

Initially, the input data is then fed into the FENN, which has a unique structure with recurrent connections that enable it to retain information from previous time steps. This allows the network to analyze temporal patterns in the data, such as changes in blink rate or head position for drowsiness, or fluctuations in breath alcohol concentration. The FENN processes these inputs through its layers, continuously updating its internal states to detect subtle signs of impairment.

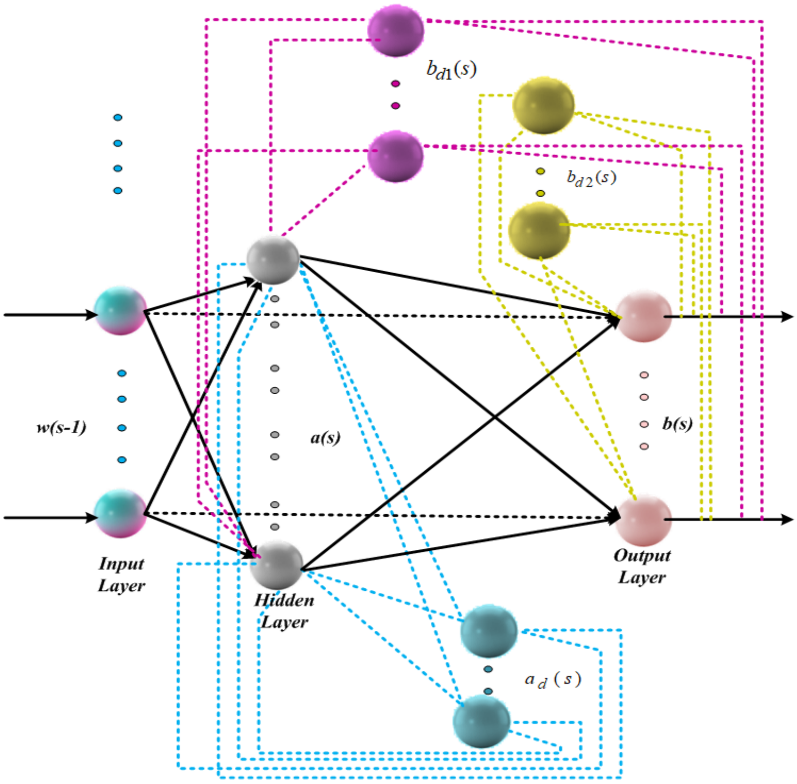

Figure 9: The Architecture of Suggested FENN Model

In a FENN, the context layer connections are fully connected, allowing each hidden neuron to be influenced by all previous hidden states enhancing the network's capacity to capture complex temporal patterns. In this manuscript, a FENN structure is developed with interconnections among the two consecutive time points of output, hidden and input layer. The FENN's mathematical model is displayed as follows in equation (2) – (6),

$$b(s) = f\left(k_2 a(s) + k_3 w(s-1) + b_{d2}(s) + y_2\right) \tag{2}$$

$$a(s) = g\left(a_d(s) + k_1 w(s-1) + b_{d1}(s) + y_1\right) \tag{3}$$

$$a_d(s) = k_4 a_d(s-1) + k_5 a(s-1) \tag{4}$$

$$b_{d1}(s) = k_6 b_{d1}(s-1) + k_7 b(s-1) \tag{5}$$

$$b_{d2}(s) = k_8 b_{d2}(s-1) + k_9 b(s-1) \tag{6}$$

where the input layer to the hidden layer, the hidden layer and the output layer, and the hidden layer and the input layer have the following connection weights, respectively, k_2, k_3, and k_1. The FENN architecture is depicted in Figure 9.

The output context layers 1 and 2, as well as the context layer for the hidden layer at s are indicated by the symbols $b_{d1}(s)$, $b_{d2}(s)$, $a_d(s)$, which specify the length of the cloudlet, the total amount of data processed, and the computation time, in that order. The bias of the hidden layer and the output layer is y_2 and y_1. Weights of the recurring relationship between the current s and $s-1$ of a_d, b_{d1} and b_{d2} are denoted by k_4, k_6, and k_8 accordingly. The connection weights of $a(s-1)$ to $a_d(s)$, $b(s-1)$ to $b_{d1}(s)$, and $b(s-1)$ to $b_{d2}(s)$ are indicated by k_5, k_7, and k_9. The vectors the hidden layer and output layer at s are denoted by $b(s)$ and $a(s)$, which expresses the task input and output size respectively, and the input layer's vector at $s-1$ is represented by $w(s-1)$. The functions that activate the output layer (represented by f) and hidden layer (represented by g) are the hyperbolic tangent sigmoid and softmax, respectively.

Based on this analysis, the network outputs a decision, such as triggering an alert if it detects signs of drowsiness or alcohol consumption. The entire process relies on FENN's ability to learn and adapt to the driver's behavior over time, improving its accuracy in real-time detection.

Red Piranha Optimization (RPO) for Enhancing FENN Parameters

In this optimization process, piranhas represent possible solutions, and their joint movements aim to explore and exploit the search space efficiently. RPO iteratively adjusts FENN parameters to reduce classification error by simulating piranhas' dynamic and aggressive hunting strategies. This results in a finely tuned neural network with improved accuracy and performance in detecting drowsiness or alcohol consumption tasks. The integration between the biologically inspired RPO and the advanced architecture of FENN ensures strong performance in recognizing and classifying the data. In the RPO algorithm, the hunting behavior of piranhas is simulated in three sequential phases, each corresponding to a specific makeover associated with feeding piranhas: searching, encircling, and attacking. A flowchart of the RPO is shown in Figure 10. The detailed progression of RPO is explained below,

Step 1: Initialization

At first, the populations of the Red Piranha fish and FENN parameters are initialized in this step. Assign appropriate initial values to the parameters in RPO algorithm.

Step 2: Random Generation

The algorithm selects the most optimal solution based on the initialized parameters. It evaluates various possibilities to select the best fit for a given problem situation.

Step 3: Fitness Function Calculation

In this, the main objective function of RPO is calculated for optimizing FENN parameters to enhance the detection of drowsiness or alcohol consumption. Also, the objective function of this RPO model is given in equation (7),

$$Fitness_{function} = [Min / Max(k, f, g)] \tag{7}$$

where, $\min/\max$ function is used for optimizing the parameters, k is denoted as the weight parameter and f, g is the activation function of FENN.

Step 4: Searching Phase

During this phase, the piranha swarm mostly explores the search space randomly, mimicking piranhas' random movement when searching for prey. This random exploration is led by "scouts," which are individual piranhas experienced in hunting and foraging. These scouts lead the team and use their knowledge to direct exploration toward useful areas of the search space. Thus, the searching and the encircling phase is represented as $R_{Search} = (i/3)I$ $R_{Ency} = (i/3)$. Where, i denotes the total number of iterations and I denote the interference value. Let the available set of (m) solutions in RPO is denoted as as S_m and the number of set of leading scouts is denoted as $\Psi = \left|\frac{m}{\xi}\right|$,where $2 \le \xi \le m$ represents the scaling factor. Then, the random individuals of Ψ is selected for the loading scouts that is denoted as $SCT = \{sct_1, sct_2, ...sct_\psi\}$. Here, position of every individual N is updated based on the n^{th} cluster scout, which has expressed in equation (8),

$$\vec{D}p_N = \left|\vec{C}.\vec{X}_{sct_n}(i) - \vec{X}_{p_N}(i)\right| \tag{8}$$

$$\vec{X}p_N(i+1) = \vec{X}_{sct_n}(i) - \vec{Q}.\vec{D}_{p_N} \tag{9}$$

$$\vec{Q} = \vec{h}_1 * \left(-2 + \vec{h}_2\right) + \left(1 - \vec{h}_1\right)\left(1 + \vec{h}_3\right) \tag{10}$$

$$\vec{C} = 2\vec{h}_4 \tag{11}$$

Where, the distance among the prey and N piranha fish is denoted as $\vec{D}p_N$, the scout position vector with n^{th} cluster is denoted as $\vec{X}_{sct_n}(i)$, the position of search agent is denoted as $\vec{X}_{P_N}(i)$ that is computed using equation (9), the coefficient vectors are denoted as $\vec{C}$, $\vec{Q}$ that is computed using equation (10 and 11) , and the random vectors are represented as $\vec{h}_1$, $\vec{h}_2$, $\vec{h}_3$ and $\vec{h}_4$,which belongs to the value as [0,1].

Step 5: Encircling Phase

When a scout piranha detects potential prey or encounters a promising solution in the search space, it emits a special signal called the "prey encircling signal" (PES). This signal acts as a communication mechanism within the swarm, indicating the existence of a promising solution. Upon receiving the PES, nearby piranhas adjust their movement to circle the promising area identified by the scouts, mimicking the circling behavior of piranhas as they approach prey. In this, the position of each herd members (albha fishes) is updated based on the distance among the individuals and prey. Thus, the distance $\vec{d}$ is computed using equation (12),

$$\vec{d} = \left|\vec{X}_{prey}(i) - \vec{X}_{P_N}(i)\right| \tag{12}$$

$$\vec{X}p_N(i+1) = \vec{d} * e^{bl}\cos(2\pi l) + \vec{X}_{prey}(i) * f + g \tag{13}$$

$$l = 1 - \frac{2 * i}{R_{Ency}} \tag{14}$$

Where, the predicted prey location at iteration i is denoted as $\vec{X}_{prey}(i)$, the position of search agent is denoted as $\vec{X}_{P_N}(i)$ that is computed using equation (13), f, g is the activation function of FENN, the constant is b, number in the particular interval [-1,1] is denoted as l that is given in equation (14).

Step 6: Attacking Phase

Once the piranha swarm has effectively encircled the promising region, indicating the possible existence of optimal solutions, the algorithm enters the attack phase. During this phase, the piranhas intensify their exploration efforts, focusing on refining solutions within the enclosed area. This phase represents the exploitation of promising solutions identified in previous phases, as piranhas focus their efforts on improving the quality of solutions and moving toward the optimal solution. Thus, attacking phase is represented using equation (15),

$$R_{Attack} = \left(i - 2 * \left[i/3\right]\right) \tag{15}$$

$$\vec{D}p_N = \left|\vec{C}.\vec{X}_{prey}(i) - \vec{X}_{p_N}(i)\right|k \tag{16}$$

$$\vec{X}p_N(i+1) = \vec{X}_{prey}(i) - \vec{Q}.\vec{D}_{p_N} \tag{17}$$

$$\vec{Q} = 2\vec{a}\vec{h}_1 - \vec{a} \tag{18}$$

$$\vec{C} = 2\vec{h}_2 \tag{19}$$

$$\vec{a} = 2 - i * \frac{2}{R_{Attack}} \tag{20}$$

Where, the position of the search agent is calculated using equation (16), predicted prey location is denoted as $\vec{X}_{prey}(i)$ that is computed using equation (17), the weight parameter is k, and the vector $\vec{a}$ is linearly decreased from the value 2 to 0, which is computed using equation (20). Also, the coefficient vector $\vec{Q}$ and $\vec{C}$ are computed using equation (18, and 19) and $\vec{Q}$ is set to the random value as [-1,1] in the attack phase.

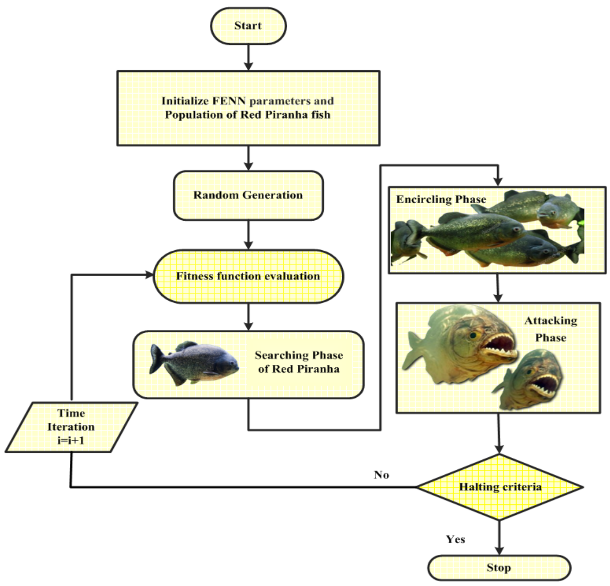

Figure 10: Flowchart of the proposed RPO

Step 7: Return the Best Optimal Solution

Step 8: Termination

Finally, RPO optimize the layers of FENN, repeating step 3 again until stopping criteria $i = i + 1$ are met. Finally, RPO optimizing FENN parameters to enhance the accuracy of detection of drowsiness or alcohol consumption and then performance metrics are analysed.

RESULTS AND DISCUSSION

The hardware and software implementation result of the proposed FENN-RPO-DACD algorithm is analyzed in this section. The hardware setup is to be a vehicle safety and control system designed to monitor the driver's condition and manage vehicle operations based on specific detections, such as alcohol consumption or drowsiness. The software implementation of the FENN-RPO-DACD methodology is carried out by MATLAB tool. This method is processed on a PC along with a Windows 10 operating system, Intel i3 core processor, and 2GB random access memory.

Hardware Simulation

The main module integrates sensors, processing, actuation, and feedback mechanisms to create a vehicle control system focused on driver safety. By continuously monitoring the driver's condition and responding in real time, the system can prevent unsafe driving conditions, such as when alcohol is detected or the driver shows signs of drowsiness, enhancing overall vehicle safety and operational control.

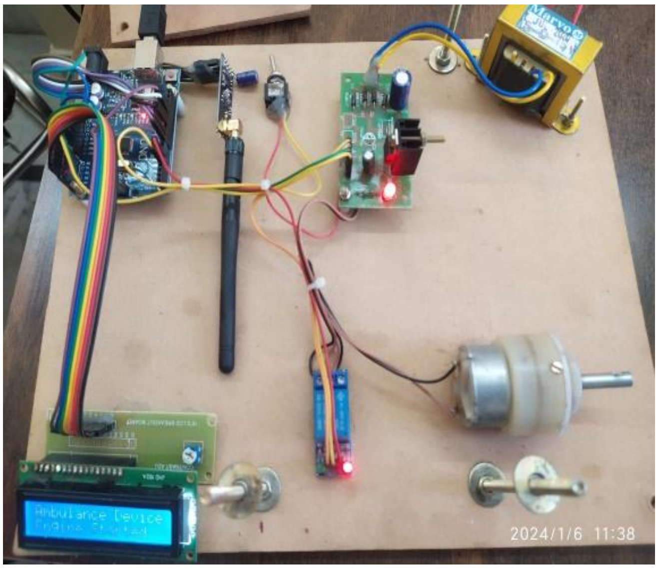

Figure 11: Hardware Setup for Ambulance Device

Figure 11 shows the hardware setup for the ambulance device. The setup appears to be an integrated control system designed for a vehicle, likely as part of a prototype or project involving automated or remotely controlled functions. At the core of the system is an Arduino Uno board, which acts as the central controller, interfaced with various components such as an LCD for status updates, a DC motor with a gearbox for mechanical actuation, and a relay module that manages high-power devices through low-power signals from the Arduino. The antenna module suggests wireless communication capabilities, possibly for remote control or data transmission using GSM, Bluetooth, or RF technologies. Power management is handled by a transformer and a voltage regulator circuit, ensuring a stable voltage supply to the components. The system is interconnected through jumper wires, connectors, and includes switches for manual control, all mounted on a board. The displayed message, "Ambulance Device Engine Started," indicates that the setup is configured for a specific application, possibly in an emergency vehicle scenario, where controlled activation of the engine and other functions are critical.

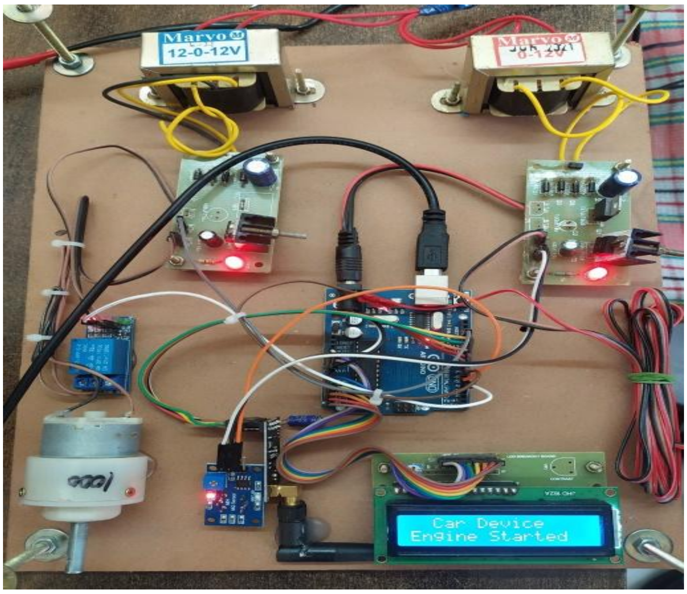

Figure 12: Hardware Setup for Car Device

Figure 12 shows that the hardware setup for car device. This setup is a sophisticated control system, likely designed for a vehicle prototype involving automation or remote control functionalities. At its core is an Arduino Uno board, which manages the entire operation, interfacing with various components such as a 16x2 LCD display for real-time status updates, and a DC motor with a gearbox, suggesting mechanical movement capabilities such as controlling wheels or similar functions. The inclusion of an antenna module hints at wireless communication, possibly via GSM or RF, enhancing the system's remote control potential. Power management is handled by two transformers labeled "Marvo 12-0-12V" and "Marvo 0-12V" along with voltage regulator circuits, ensuring stable operation of all components. Relay modules enable the control of high-power devices using the Arduino's low-power signals, making it versatile for various actuation tasks. Interconnected by an array of jumper wires, ribbon cables, switches, and connectors, this system is meticulously designed to manage power efficiently and execute automated controls, making it ideal for applications in automated vehicle control or other complex mechanical systems.

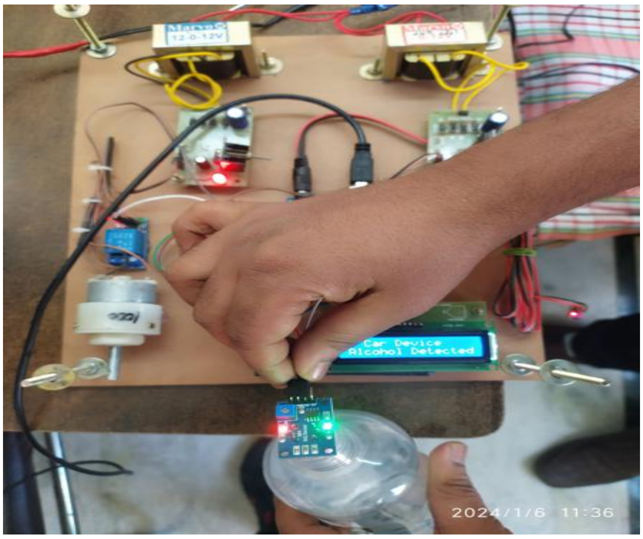

Figure 13: Hardware Setup for Detecting Alcohol Consumption

Figure 13 shows that the hardware setup for detecting alcohol consumption. This setup is a prototype of an alcohol detection system designed for integration into vehicles, potentially to enhance safety by monitoring the driver's condition before engine activation. At its core, an Arduino Uno board controls and manages the connected components, including an alcohol sensor module (likely MQ-3 or similar) that detects alcohol levels in the air. The detected data is processed by the Arduino and displayed on a 16x2 LCD screen, which shows messages such as "Car Device Alcohol Detected." The system includes a DC motor with a gearbox, possibly for actuation or vehicle-related functions, and a relay module that controls high-power devices based on sensor readings, further enhancing the system's automation capabilities. Power management is achieved through two transformers and voltage regulator circuits that stabilize and provide appropriate voltages for the entire setup. The interconnected network of jumper wires, ribbon cables, switches, and connectors ensures seamless communication and control among all modules, highlighting the prototype's focus on safety and automation in vehicular applications.

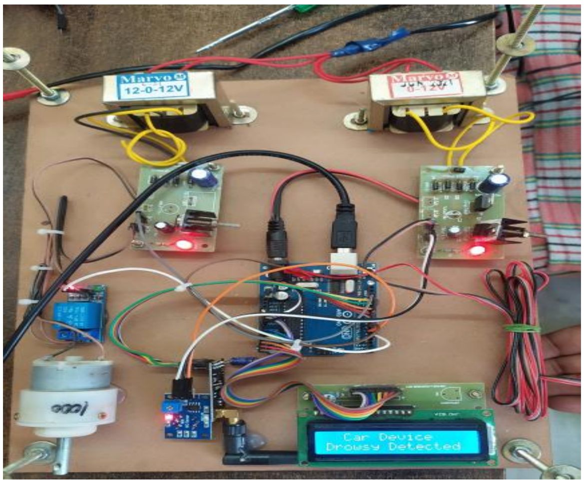

Figure 14: Hardware Setup for Detecting Drowsiness

Figure 14 shows that the hardware setup for detecting drowsiness. This setup appears to be a prototype for a drowsiness detection system designed for vehicles, incorporating various components for monitoring and control. At the core is an Arduino Uno board, which serves as the main microcontroller, interfacing with other modules. A 16x2 LCD display shows the message "Car Device Drowsy Detected," indicating the system's status. The setup includes a DC motor with a gearbox at the bottom left, potentially for simulating vehicle actuation. A relay module, positioned near the motor, manages high-power devices, allowing the Arduino to control them with low-power signals. Two transformers labeled “Marvo 12-0-12V” and “Marvo 0-12V” handle voltage step-up or step-down, managing the power supply across the system. Voltage regulator circuits are visible near the transformers, stabilizing and regulating the voltage. Additionally, the setup includes jumper wires, ribbon cables, switches, and connectors for seamless communication between all components, making it a cohesive system aimed at detecting driver drowsiness and responding accordingly to enhance vehicle safety.

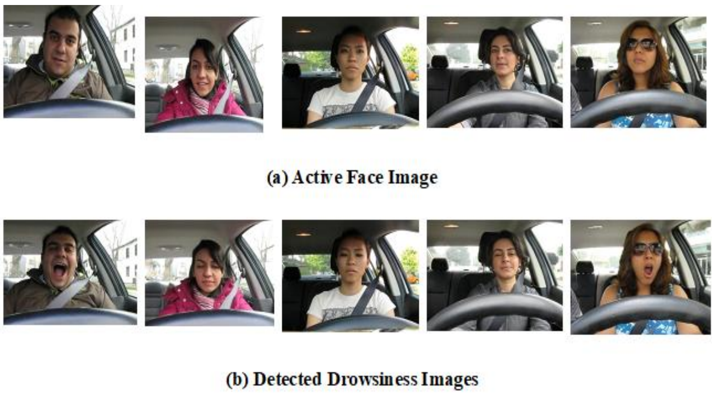

Figure 15: Representation of Active and Sleepy Driver Faces

In figure 15, the Active and Sleepy Driver Faces are shown. Here, the proposed FENN-RPO-DACD model demonstrates its effectiveness in accurately detecting driver drowsiness from the collected images. This detection capability is crucial for enhancing road safety by preventing accidents due to driver fatigue.

Performance Measures using Software Simulation

In this case, the effectiveness of the proposed method is evaluated through various performance metrics, including Accuracy, F-measure, False Acceptance Rate (FAR), Receiver Operating Characteristic (ROC) curve, Sensitivity, False

Negative Rate (FNR), Precision, False Positive Rate (FPR), Specificity, and Computational Time. It needs parameters like True Negative $(T(N))$, True Positive $(T(P))$, False Negative $(F(N))$, and False Positive $(F(P))$.

Accuracy Calculation

It measures the effectiveness of a classification model in accurately detecting DAC into correct categories, as expressed in equation (21).

$$Accuracy = \frac{T(P)+T(N)}{T(P)+T(N)+F(P)+F(N)} \tag{21}$$

Precision Calculation

It estimates the extent of accurately anticipated positive examples out of all emphatically predicted samples, which is registered utilizing an equation (22),

$$\Pr = \frac{T(P)}{T(P)+T(N)} \tag{22}$$

Calculation of Recall

It measures the quantity of appropriately prophesied positive models out of entire true positive models in the given dataset. Equation (23) shows the calculation formula of recall.

$$\mathrm{Re} = \frac{T(P)}{T(P)+F(N)} \tag{23}$$

Calculation of F-measure

It is often used when there is an imbalance among the positive as well as negative samples or when there is a need to prioritize both precision and recall equally. Equation (24) shows the calculation formula of F-measure.

$$F-measure = \frac{2(\mathrm{Re}\times \Pr)}{\mathrm{Re}+\Pr} \tag{24}$$

Computation of FAR

The ratio of false alerts to the total number of normal occurrences is known as the false alarm rate. It is computed using equation (25),

$$FAR = \frac{FP}{FP+TN} \tag{25}$$

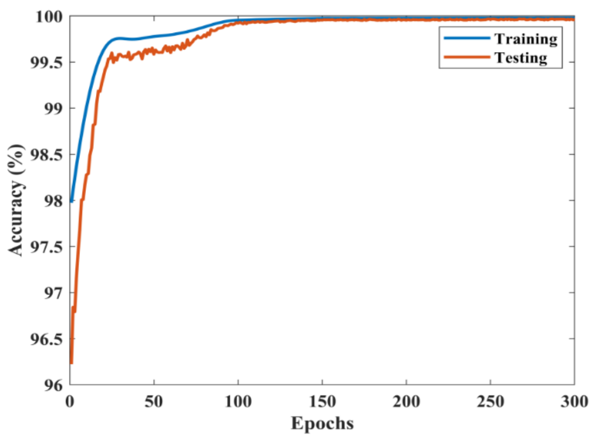

Figure 16: Accuracy for FENN-RPO-DACD using Sensed Data

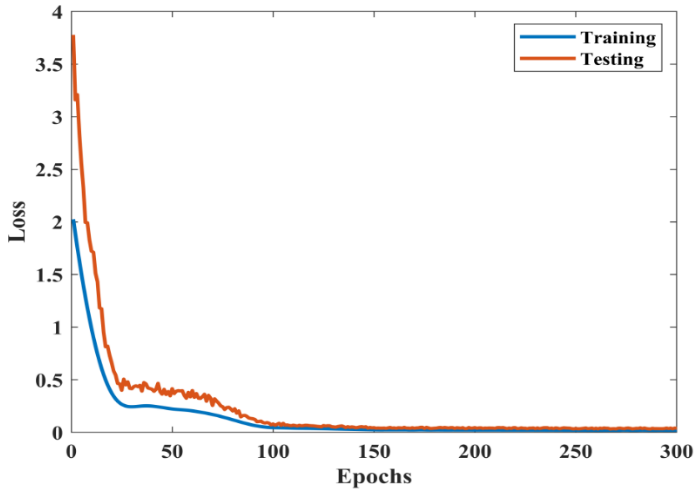

Figure 17: Loss for FENN-RPO-DACD using the Sensed Data

Figure 16 and Figure 17 show the connection between accuracy and loss for the FENN-RPO-DACD calculation when applied to the sensed data by roadside device. As the preparation advances, the accuracy improve while the loss diminishes, showing successful learning and model intermingling.

Comparative analysis

In this section, the evaluation analysis like Accuracy, FAR, Precision, FNR, Sensitivity, FPR, Specificity, F-measure, ROC, and Computational Time of FENN-RPO-DACD methodology are compared with existing approaches like O-SNN-DADSS [21], AI-SIoT [22], and CNN [23] methods respectively.

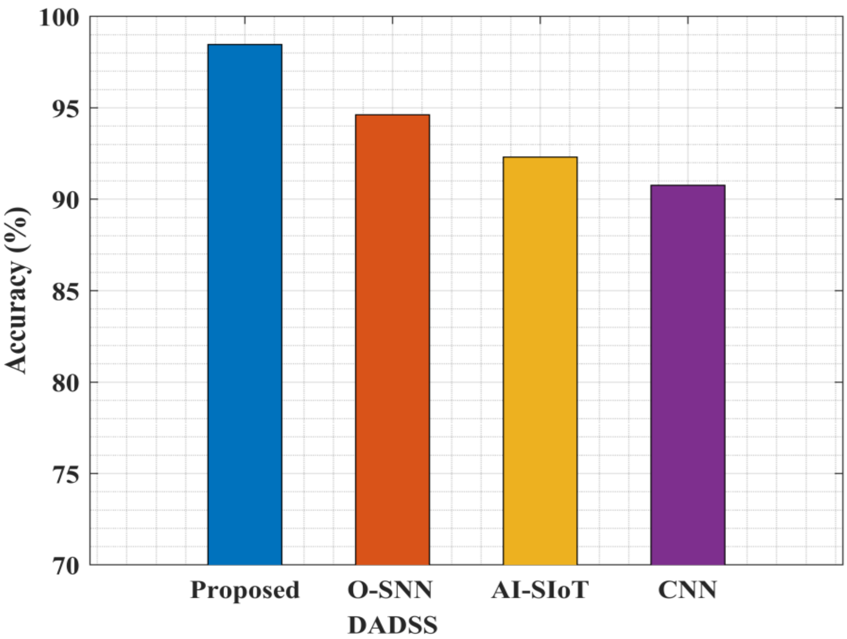

Figure 18: Performance Analysis of Accuracy

The accuracy comparative assessment is shown in Figure 18. In this, the FENN-RPO-DACD method attains 18.98%, 21.56%, and 24.96% higher accuracy than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

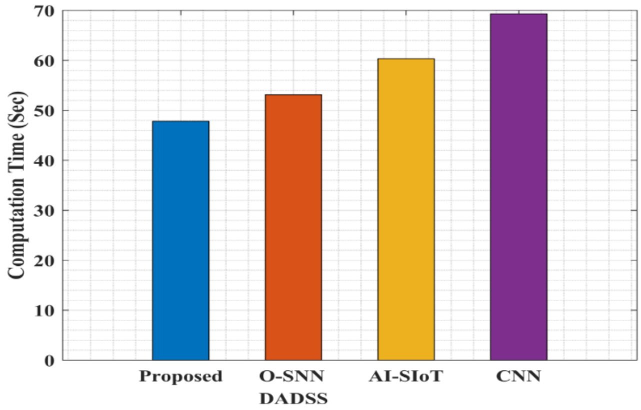

Figure 19: Performance Analysis of Computation Time

The computation time comparative assessment is shown in Figure 19. In this, the FENN-RPO-DACD method attains 12.39%, 19.56%, and 29.67% higher Computation Time than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

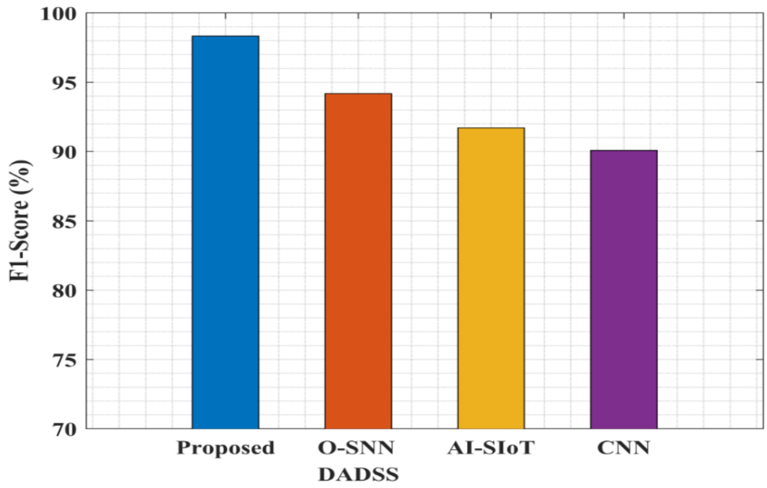

Figure 20: Performance Analysis of F1-Score

The F1-score comparative assessment is shown in Figure 20. In this, the FENN-RPO-DACD method attains 22.78%, 26.34%, and 30.23% improved F1-Score than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

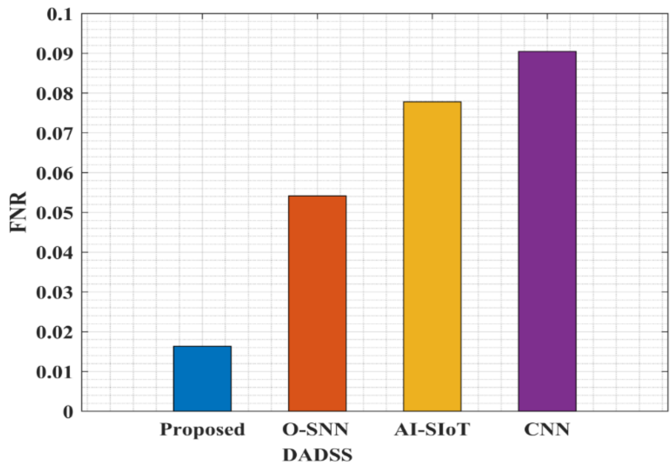

Figure 21: Comparative Analysis of FNR

The FNR comparative assessment is shown in Figure 21. In this, the FENN-RPO-DACD method attains 29.78%, 34.89%, and 38.96% lower FNR than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

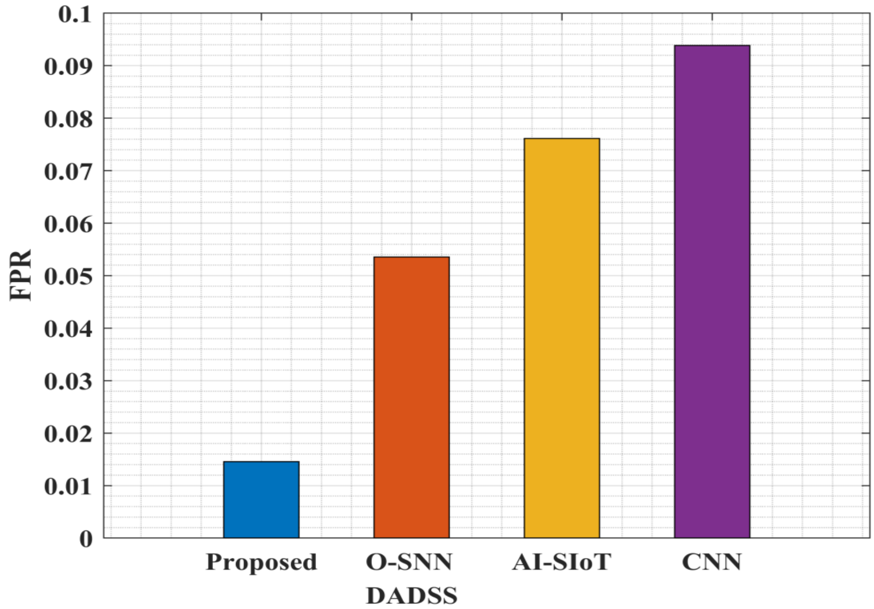

Figure 22: Performance Analysis of FPR

The FPR comparative assessment is shown in Figure 22. In this, the FENN-RPO-DACD method attains 28.78%, 34.14%, and 38.67% lower FPR than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

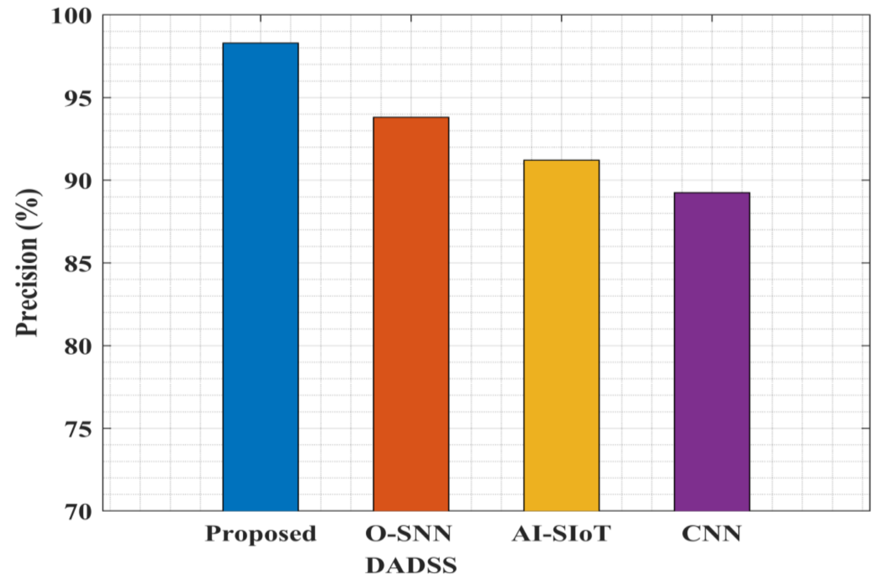

Figure 23: Performance Analysis of Precision

The precision comparative assessment is shown in Figure 23. In this, the FENN-RPO-DACD method attains 18.97%, 21.56%, and 24.38% higher precision than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

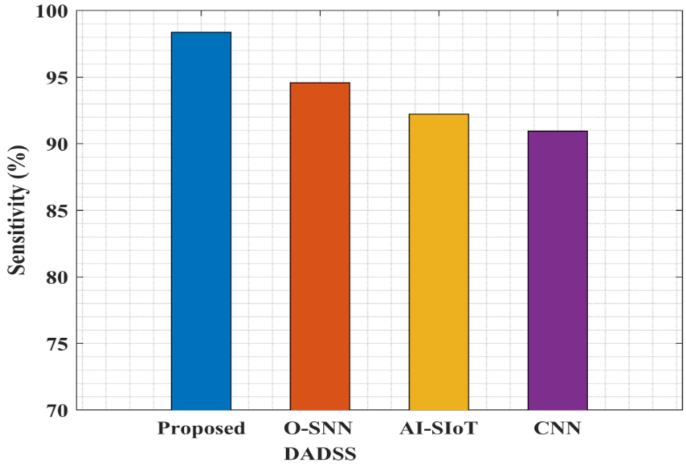

Figure 24: Performance Analysis of Sensitivity

The sensitivity comparative assessment is shown in Figure 24. In this, the FENN-RPO-DACD method attains 14.98%, 18.67%, and 21.09% higher sensitivity than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

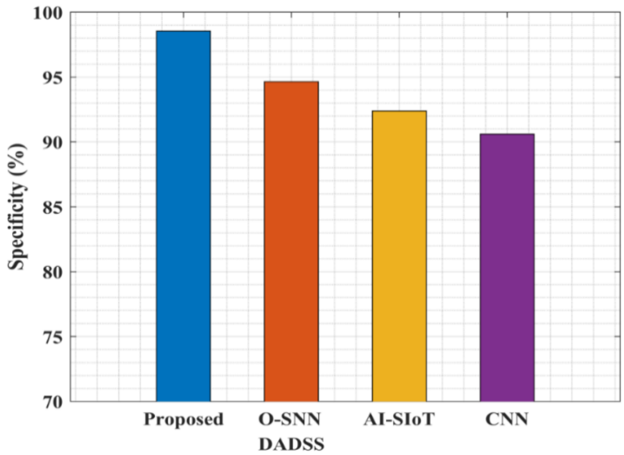

Figure 25: Comparative Investigation of Specificity

The specificity comparative assessment is shown in Figure 25. In this, the FENN-RPO-DACD method attains 17.8%, 20.78%, and 22.98% improved specificity than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively.

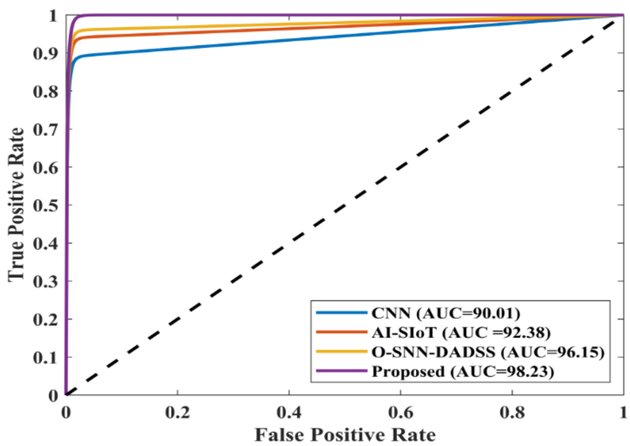

Figure 26: Analysis of ROC Performance

Figure 26 shows the computation time analysis. In this instance, the effectiveness of the suggested SyF-FL-FENN-APP method provides 7.11%, 5.27%, and 3.33% higher AUC in contrast to currently used methods such as O-SNN-DADSS, AI-SIoT, and CNN respectively.

CONCLUSION

In this manuscript, an AI-enabled DACD using Fully Elman Neural Network with Red Piranha Optimization for IoT based smart cities is successfully implemented. Initially, the IoT kit consists of several normal cars, ambulance cars, and roadside devices. The roadside devices which are transceivers fixed at predetermined locations, relay information to both normal and ambulance car devices. The data collected by the IoT kit is preprocessed using the MaxAbsScaler Normalization approach. After that, the FENN is applied in the preprocessed data to validate the detection results. Also, RPO is proposed for enhancing the weight parameters of FENN. By then the implementation of FENN-RPO-DACD is done by the MATLAB platform, and the outcomes are compared with other conventional techniques. Thus, the proposed FENN-RPO-DACD method has achieved 22.65%, 26.45%, and 30.09% higher F1-Score, 29.78%, 34.89%, and 38.96% lower FNR, 17.8%, 20.78%, and 22.98% higher specificity, 7.11%, 5.27%, and 3.33% higher AUC than other conventional techniques like O-SNN-DADSS, AI-SIoT, and CNN respectively. In the future, privacy concerns will be addressed by integrating data encryption and anonymization techniques with the FENN model. This approach will ensure that sensitive information is protected while still enabling effective monitoring and detection.

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