Urban Traffic Incident Detection based on an Improved Extreme Learning Machine Algorithm

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Abstract: - Incidents on urban roads are the primary cause of well-known problems, including traffic congestion, pollution, and travel delays. Hence, Fast incident detection is necessary for improved real-time management. This paper proposes an automatic incident detection (AID) algorithm that hybridizes the Particle Swarm Optimization (PSO) algorithm with the regularized Extreme Learning Machine (RELM). The PSO is used to optimize the initial matrix weights and output thresholds. This leads to enhanced detection accuracy and rapidity. The proposed algorithm achieves a fast and good detection performance compared to Support Vector Machine (SVM), Random Forest (RF), and standard ELM.

Key-Words: - Incident Detection, Extreme Learning Machine, Particle swarm optimization, Urban roads, Machine learning, Simulation of urban road mobility.

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1 Introduction

The main causes of increased levels of congestion, pollution, and road user stress are traffic accidents and incidents in general, when they are not monitored in real time. Both financial loss and a risk to public safety may arise from this. The ability to build an intelligent transportation system that recognizes interruptions and predicts traffic situations to enhance and adjust operational activities has been made possible by developments in computer and data technology. Loop detectors are used in most of the employed approaches [1], [2] to detect traffic incidents. However, these techniques have several disadvantages, such as the high cost and the detection being influenced by poor weather conditions. Another technique uses comparative algorithms [3] based on predefined thresholds representing normal traffic conditions. A family of algorithms is the statistical Algorithms [4], which use statistical algorithms to estimate the traffic state, which is compared with the measured traffic state. The existence of a statistical difference indicates the existence of incidents. The limitations of these algorithms are their dependence on the detectors. Thus, the performance of these algorithms will be affected by the defects in detectors and require extensive computation. With the development of Artificial Intelligence, Machine learning methods are increasingly reliable in transportation systems, [5], [6]. These algorithms include RF, Neural Networks (NN) and SVM. Among the limitations of these cited algorithms, either requires significant time in the training process, or performance is inferior. The method proposed in this study for incident detection is based on the ELM [7], [8], which employs a distinctive approach where it randomly assigns input weights without any iterative adjustments and calculates output weights through the use of the Moore-Penrose (MP) generalized inverse matrix. This methodology results in ELM offering advantages in terms of faster training speed, robust generalization capabilities, and a reduced risk of getting stuck in local minima. The hidden layer nodes of ELM have randomly generated parameters based on a continuous probability distribution, and these parameters remain independent of the training samples. ELM exhibits limited control capacity as it directly computes minimum norm least-squares solutions, [9]. To mitigate these challenges, [9] introduced the R-ELM. The effectiveness of this algorithm hinges on the selection of the regularization parameter, a task typically carried out by experienced practitioners through trial and error or by employing optimization techniques documented in the literature. For instance, classical methods such as Cross-Validation and the coordinate descent approach have been traditionally utilized to determine the optimal regularization parameter in numerous studies in the literature. Various alternative approaches have been suggested to determine the suitable value. However, it's worth noting that this method elevates computational complexity due to the need for iterative large matrix inversions. In response to this challenge, we introduce for incident detection a novel Regularized ELM algorithm that employs the PSO method to optimize the regularization parameter and ensure fast and good performance in urban road incident detection. The rest of this study is structured as follows: The data collection and incident detection methodology for urban roadways are presented in Section 2. The proposed hybrid model for incident detection is presented in Section 3. Section 4 presents the simulation results. Finally, the conclusion is given in section 5.

2 Incident Detection Methodology

2.1 Automatic Incident Detection Systems

One technique for identifying incidents or unusual circumstances on roadways is the AID system, which typically uses a mix of cameras, sensors, and algorithms to detect potential events in real time, such as traffic jams or accidents. A variety of AID system types are available, such as loop finders, [10]. These systems use embedded sensors in the road to identify changes. They can identify slow-moving traffic and congestion. [11] in the video. These systems record traffic on camera by placing cameras above the road. Real-time video analysis is performed using algorithms [12], [13] to detect situations such as collisions or cars going the wrong way. Congestion and occurrences beyond a video camera's field of vision can be detected by them. The AID system can automatically notify traffic management systems of incidents, enabling them to respond appropriately. AID systems can help speed up incident reaction times and enhance traffic flow, both of which can eventually increase road safety and lessen traffic. The traffic data needed to assess whether an event is present or absent is given to the system via traffic detection. These data are usually supplied periodically and comprise speed, volume, and occupancy, [14].

2.2 Data Collection

The fundamental metric of the detection method is the examination of changes in traffic data. To illustrate traffic conditions, such as velocity, occupancy rate, Illustration of a road incident and traffic flow, a variety of traffic statistics can be used. In this study, traffic and incident data measurements were generated using the SUMO simulator. Subsequent analysis was conducted on both the training and validation sets, with incident detection specifically applied to the test set. Inductive loop detectors captured traffic dynamics, providing measurements at a 30-second resolution for speed, volume, and occupancy. Speed denotes the average speed of vehicles within a 30-second window for each lane, volume signifies the count of vehicles passing through each lane, and occupancy represents the proportion of time during the detection window that the detector was occupied by vehicles.Figure 1 illustrates how such a road incident can affect these traffic parameters and cause changes in speed, flow and lane occupancy.

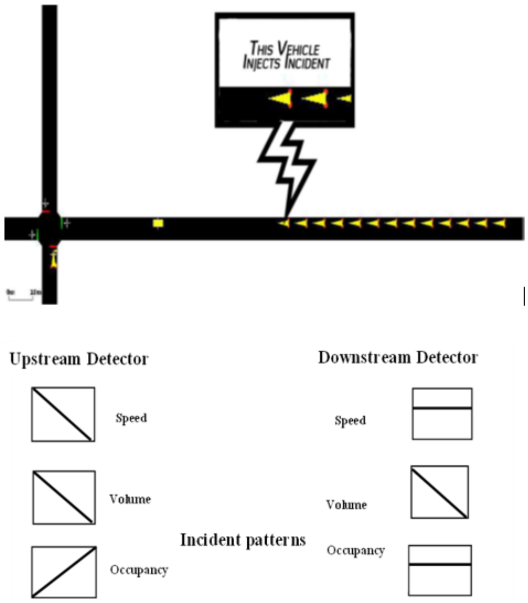

Fig. 1: Illustration of a road incident
Source: created by the authors

Every flow in the upstream and downstream loop detectors exhibits a unique traffic pattern during a traffic incident. Expected changes: decrease in upstream speed and volume; decreased downstream volume. At the same time, upstream occupancy is rising together with downstream speed and occupancy changes.

Velocity is the average speed of all vehicles that pass a given detection site over a predetermined amount of time. Equation (1) describes how V is computed.

$$V = \frac{\sum_{i=1}^{N} V_i}{N} \quad (1)$$

N is the number of vehicles at a detection location over a given period, and V_i is the i$^{\text{th}}$ velocity.
Occupancy rate is computed as outlined in equation (2).

$$O = \frac{\sum_{i=1}^{N} L_i}{L} \quad (2)$$

L is the observed road length, and L_i is the length of the i^{th} vehicle.
The number of cars that pass through a detection point in a predetermined time is referred to as the traffic flow (T).

$$T = \frac{\sum_{i=0}^{\tau} N_i}{\tau} \quad (3)$$

where τ is the time interval, and N_i is the number of vehicles seen at a detection location within a 1-second interval.

3 Prepare Design of Incident Detection Model based on a Hybrid Regularized ELM and PSO

3.1 Extreme Learning Machine

[15] presented an innovative method known as ELM for SLFNs that simplifies the network design by requiring the determination of only the output weights. Unlike other methods that require either manual configuration or computationally intensive parameter tuning, ELM takes a distinctive approach. It randomly assigns the hidden neuron parameters, and the output weights are determined analytically using the MP generalized inverse, [16]. This unique methodology ensures that the parameters within the hidden layer remain uncorrelated with the training samples [15]. Let's consider N distinct training $\{(\boldsymbol{x_i}, \boldsymbol{t_i})\}_{i=1}^{N}$, where $\boldsymbol{x_i}$=[$\boldsymbol{x_{i1}}$,$\boldsymbol{x_{i2}}$,….$\boldsymbol{x_{in}}$]T and $\boldsymbol{t_i}$ = [$\boldsymbol{t_{i1}}$,$\boldsymbol{t_{i2}}$,……..,$\boldsymbol{t_{im}}$]T an $\boldsymbol{l} \times \boldsymbol{n}$ weight matrix $\boldsymbol{w}$, where $\boldsymbol{w_j}$=[$\boldsymbol{w_{j1}}$,$\boldsymbol{w_{j2}}$,….$\boldsymbol{w_{jn}}$]T. The vector $\boldsymbol{b}$ is $\boldsymbol{l} \times \boldsymbol{1}$ hidden bias vector corresponding to every hidden neuron. Additionally, the output and the hidden layers are connected through an $\boldsymbol{l} \times \boldsymbol{m}$ matrix $\boldsymbol{\beta}$, where $\boldsymbol{\beta_j}$=[$\boldsymbol{\beta_{j1}}$, $\boldsymbol{\beta_{j2}}$,…..,$\boldsymbol{\beta_{jm}}$]T. The ELM structural configuration can be described as follows:

$$\boldsymbol{t_i}=\sum_{j=1}^{l} \boldsymbol{\beta_j} g(\boldsymbol{w_j}.\boldsymbol{x_i}+\boldsymbol{b_j}); \boldsymbol{i = 1, 2, \ldots\ldots, N} \quad (4)$$

where $\boldsymbol{j} \in \{\boldsymbol{1, 2, \ldots\ldots, l}\}$,$\boldsymbol{w_i}.\boldsymbol{x_i}$ indicates the inner product of $\boldsymbol{w_j}$and $\boldsymbol{x_i}$. The function g(x) serves as an activation function. Equation (4) can be presented:

$$\boldsymbol{H\beta = T} \quad (5)$$

Here, $\boldsymbol{H}$ is the hidden layer. $\boldsymbol{T}$ represents the output matrix, $\boldsymbol{T}$=[$\boldsymbol{t_1}$,$\boldsymbol{t_2}$;……;$\boldsymbol{t_N}$]T

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{g(w_1.x_1 + b_1)} \ldots & \boldsymbol{g(w_l.x_1 + b_l)} \\ \boldsymbol{g(w_1.x_N + b_1)} \ldots & \boldsymbol{g(w_l.x_N + b_l)} \end{bmatrix} \quad (6)$$

The exclusive minimum norm least square solution $\boldsymbol{\beta}$ is as follows:

$$\boldsymbol{\beta = H^{+}T} \quad (7)$$

where $\boldsymbol{H^{+}}$ represents the Moore-Penrose (MP) generalized inverse of matrix **H.**

3.2 Regularized Extreme Learning Machine (R-ELM)

ELM has proven to be a successful choice due to its remarkably rapid training pace and commendable generalization capabilities. However, it's important to note that ELM still aligns with the empirical risk minimization concept and tends to produce overfit models, as highlighted in [9]. Furthermore, it could lead to less robust estimates, particularly in scenarios with data outliers or heteroscedasticity. Lastly, ELM is limited in its control capacity because it directly computes minimum-norm least-squares solutions. R-ELM [9] utilizes Structural Risk Minimization (SRM). Typically, in the training of an SLFN, the objective is to determine the values of w_i ,b_i , β $(i = 1,2, \ldots\ldots l)$ with:

$$\begin{gathered} \mathrm{Min}\|\varepsilon\|^2 \\ s.t \sum_{j=0}^{l} \beta_j\, g(w_j.x_i + b_j)\text{-}t_i = \varepsilon_i; \\ i = 1,2, \ldots\ldots\ldots.., N \end{gathered} \quad (8)$$

Here ε_i =[$\varepsilon_{i1}, \varepsilon_{i2}, \ldots\ldots\ldots \varepsilon_{im}$] signifies the residual between the target value and the actual value of the ith sample. However, a model with strong generalization capabilities should strike the optimal balance between the empirical and structural risks, which collectively constitute the true prediction risk by statistical learning theory. The balance between these risks can be fine-tuned by incorporating a weighting factor γ for the empirical risk, signified by the sum of squared errors $\|\varepsilon\|^2$. Simultaneously, the structural risk is expressed through $\|\beta\|^2$, obtained by maximizing the distance between the class boundaries. Furthermore, to obtain a reliable estimate that mitigates the impact of outliers, the $error$ ε_i is proportional to the variable v_i. Consequently, $\|\varepsilon\|^2$ is expanded to $\|D\varepsilon\|2$ where D $= diag(v_1, v_2, \ldots\ldots, v_N)$. As a result, the R-ELM mathematical model can be described as follows:

$$\begin{gathered} \min \frac{1}{2}\|\beta\|^2 + \frac{1}{2}\gamma\|D\varepsilon\|^2 \\ s.t \sum_{j=0}^{l} \beta_j\, g(w_j.x_i + b_j)\text{-}t_i = \varepsilon_i; \\ i = 1,2, \ldots\ldots\ldots\ldots.., N \end{gathered} \quad (9)$$

By manipulating the parameter γ, we can fine-tune the balance between empirical and structural risk. This adjustment enables us to achieve an optimal trade-off between these two types of risks, ultimately leading to a model exhibiting the most refined generalization performance. The Lagrangian for Equation (6) is given by:

$$L = (\beta , \varepsilon , \alpha) = \frac{\gamma}{2}\ \|D\varepsilon\|^2 + \frac{1}{2}\|\beta\|^2 - \sum_{i=1}^{N} \alpha_i \left(\sum_{j=1}^{l} \beta_j\, g(w_j . x_i + b_j) - t_i = \varepsilon_i\right) = \frac{\gamma}{2}\ \|D\varepsilon\|^2 + \frac{1}{2}\|\beta\|^2 - \alpha(H\beta - T - \varepsilon) \quad (10)$$

where $\alpha_i \in \mathbb{R}(i = 1,2, \ldots\ldots, N)$ represents the Lagrangian multiplier associated with the equality constraint of Equation (6) and $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_N]$.

The optimality conditions are:

$$\begin{cases} \frac{\partial L}{\partial \beta} \rightarrow \beta^T = \alpha H , \\ \frac{\partial L}{\partial \varepsilon} \rightarrow \gamma \varepsilon^T D^2 + \alpha = 0, \\ \frac{\partial l}{\partial \alpha} \rightarrow H\beta - T - \varepsilon = 0. \end{cases} \quad (11)$$

By plugging in the final expressions from Equation (8) into the second expression, we can derive a clear and explicit formula for α as described in Equation (15) and calculate $\varepsilon_i$using α as specified in Equation (15).

$$\alpha = -\gamma(H\beta - T)^T \quad (12)$$

$$\varepsilon_i = \frac{\alpha_i}{\gamma} \quad (13)$$

Solving Equation (8) allows us to derive the solution for β

$$\beta = (\frac{I}{\gamma} + H^T D^2 H)^{+}\ H^T D^2 T \quad (14)$$

Here, I represents the unit matrix.

where D represents the unit matrix. The value of I , β can be computed using the following expression:

$$\beta = \left(\frac{I}{\gamma} + H^T H\right)^{+} H^T T \quad (15)$$

The conventional ELM can be regarded as a specific instance of Unweighted Regularized ELM when the parameter $\gamma \rightarrow \infty$. Various methods for computing the weights v_i , such as those described in [15], can be employed to determine them.

$$v_i = \begin{cases} 1 & \left|\frac{\varepsilon_i}{\hat{s}}\right| \leq C_1 \\ \frac{c_2 - \left|\frac{\varepsilon_i}{\hat{s}}\right|}{c_2 - c_1} & C_1 \leq \left|\frac{\varepsilon_i}{\hat{s}}\right| \leq C_2 \\ 10^{-4} & Otherwise \end{cases} \quad (16)$$

where the constants C_1 and C_2 are commonly chosen as 2.5 and 3, respectively, as indicated in [9].

$\hat{s}$ Represents a reliable assessment of the deviation standard for the error variables ε_i and can be determined as follows:

$$\hat{s} = \frac{IQR}{2 \times 0.6745} \quad (17)$$

where IQR refers to the interquartile range.

3.3 Hybrid PSO-RELM Model for Incident Detection

The choice of the regularization parameter is of utmost importance for improving generalization performance. In this study, we introduce the PSO-RELM algorithm for incident detection. We leverage the PSO algorithm to determine the optimal value of the regularization parameter. PSO, a stochastic global optimization technique rooted in swarm intelligence, iteratively improves a candidate solution using a predefined quality metric, [17]. It leverages a population of candidate solutions referred to as "particles" to iteratively converge on a solution optimized for the problem at hand. The movement of these particles within the search-space is governed by mathematical equations that dictate their position (as described in Equation (18)) and velocity (as denoted in Equation (19))

$$x_{i,d}(t + 1) = v_{i,d}(t + 1) + x_{i,d}(t) 1 \ \leq i \leq n\ ;\ 1 \leq d \leq D \quad (18)$$

$$v_{i,d}(t + 1) = x_{i,d}(t) + C_1 r\big[p_{i,b}(t) - x_{i,d}(t)\big] + C_2 r[g_{i,b}(t) - x_{i,d}(t)] \quad (19)$$

Here, C_1 and C_2 denote positive acceleration constants, and r is a random number generated within the range of 0 to 1. $g_{i,b}$ represents the best position among neighbors, $p_{i,b}$ is the best position of the ith particle, D represents the dimension of the search space, and n denotes the overall particle count. There are two important considerations when applying the PSO algorithm:

The representation of particles and the choice of fitness function.

The steps of the proposed PSO-RELM algorithm can be encapsulated as follows:

Considering a training set N $= \{(x_i, t_i) | x_i \in \mathbb{R}^n , t_i \in \mathbb{R}^m , i = 1, \ldots\ldots\ldots, N\}$, an activation function $f(x)$, and several hidden nodes H.

Algorithm 1 illustrates the proposed Hybrid PSO-RELM model for incident detection.

ALGORITHME1: Hybrid PSO-RELM model

Step 1: Initialize PSO: Each particle encodes ELM parameters: input weights W_{ij} randomly, bias b_i, and γ from the set $\{2^{-20},: : :,2^{20}\}$.

Step 2: Train ELM: for each particle, compute the output matrix Z using the activation function f(x) and input weights.

- Compute the predicted output Y.
- Compute the error, using the predicted and the actual outputs.
- Update the weights W_{ij} using the error and the regularization parameter.
- Update the bias b_i.
- Update the regularization parameter γ using the error.

Step 3: Evaluate Fitness, Update Particles and Iterate:

- Calculate the fitness for each particle using a fitness function as: Mean Squared Error (MSE) on training data.
- Update position & velocity based on best positions using respectively equations (18) and (19).
- Repeat until convergence or max iterations.

Step 4: Identify the optimal regularization parameter $\gamma_{optimal}$ to choose effective incident detection model.

4 Simulation Results

4.1 Performance Evaluation Criteria

Mean time to detection (MTTD), false alarm rate (FAR) [18], and detection rate (DR) are three of the main performance standards for AID. Their definitions correspond to those given in [19]. The percentage of reported incident cases that are accurately identified among all documented incident reports acknowledged as having occurred is known as the detection rate (DR). It also states that the incident must be detected by the algorithm within a short time (4 minutes, for example) of its onset. If the algorithm is unable to identify the incident throughout this period, it will be classified as undetected:

$$DR = \frac{Number\ of\ incidents\ detected}{Total\ number\ of\ incidents\ cases} \times 100\% \quad (20)$$

$$FAR = \frac{Number\ of\ detection\ false\ alarms}{Number\ of\ detected\ incidents} \times 100\% \quad (21)$$

MTTD: In a set of (n) events, the TTD (the amount of time it takes to find an incident) is determined by taking the difference in time between the incident's actual occurrence (t_iocc) and the algorithm's identification of it (t_ialg):

$$MTTD = \frac{1}{n}\sum_{i=1}^{n} t_{ialg} - t_{iocc} \quad (22)$$

The SUMO Simulator's sensors provide traffic statistics, which include traffic flow, occupancy, and speed.

4.2 Simulation of Urban Road Mobility (SUMO)

The term SUMO refers to the modeling and analysis of several facets of transportation and mobility in urban settings using computer-based simulation methods. To investigate and forecast the motion and exchanges of various entities within the city, this method entails building virtual models of metropolitan regions, that encompass their public transportation systems, road networks, people, cars, and other relevant aspects. This approach is well known in the research community and has received an abundance of attention, as seen by the large amount of scientific literature that it has appeared in [20]. In addition to the features already covered, it allows smooth communication with external programs while running by using Traci (Traffic Control Interface). Access to SUMO enabled by the client/server TCP architecture used in this interface. The simulation data can be examined to learn more about trip times, congestion points, traffic patterns, and other relevant information. Visualization tools aid in clearly presenting results.

4.3 The Scenario used in the Simulation

The "Original Urban Network Scenario" simulates a traffic situation where upstream and downstream detector stations are arranged at a crossroads or traffic lights. This simulation faithfully captures a scenario in which crossroads are frequently encountered in an urban transportation network. This is especially important to keep in mind when setting up two stations in an incident management system. It is expected that the detectors in this configuration will be placed just in front of intersections. Two detectors are positioned along a continuous link in a two-station arrangement: one upstream, in front of the traffic intersection that connects the two links, and one downstream, in front of the downstream crossroad at the end of the subsequent link. Notably, the recorded traffic data, including parameters obtained from these detectors, is expected to be significantly affected by traffic signals.

4.4 Results Analysis

The selected input features for classification consist of traffic flow, occupancy rate, and velocity that are taken from inductive loop detectors located upstream and downstream. The algorithms produce two outputs: one for an incident and zero for a non-incident. There were three distinct incident locations. 60, 400, and 600 meters from reference points have data recorded every 30 seconds. The dataset consists of 5752 samples. Among them, 3000 of these incident cases are collected at the exact time of occurrence of incidents and 20 % (1150 samples) of the total dataset was reserved for testing, with 575 samples for the incident class and 575 samples for the non-incidents class. The rest (4602 samples) was reserved for training. with 2425 samples for the incident class and 2177 samples for the non-incidents class.

This indicates a class imbalance, which is a common challenge in traffic incident detection problems. Such imbalance may bias the learning process toward the majority (incident) class. SMOTE was applied to the training set to balance the classes, increasing the number of minority class samples from 2,177 to 2,425, resulting in a total of 4,850 training samples.

After applying SMOTE to the training set, 5-fold stratified cross-validation was conducted. Synthetic minority class samples were generated only for the training folds in each iteration, and model performance was evaluated on the untouched validation folds.

To determine the regularization parameter for R-ELM, it is appropriately selected to attain satisfactory generalization performance within the range [$\mathbf{2^{-20}}$, …$\mathbf{2^{20}}$]. In this context, 40 distinct values for are considered. After multiple tests, we opt for $\boldsymbol{\gamma_{optimal}} = \mathbf{2^{-2}}$. Alternatively, for the implementation of the PSO-RELM algorithm, the regularization parameter is chosen from the interval [$\mathbf{2^{-20}}$,…..,$\mathbf{2^{20}}$]. The population size and the number of iterations for the PSO algorithm are set to 10 and 40, respectively. The algorithm yields an optimal value of 0.2391 after 40 iterations.

The values of parameters: $C_1 = 1{,}5$, $C_2 = 1{,}5$ and r=0,5. The effectiveness of these parameter settings and the comparative performance of the proposed approach against SVM, RF, ELM, and R-ELM models are presented in Table 1.

Table 1. Results obtained for incident detection using SVM, RF, ELM, R_ELM, and PSO_RELM.

Algorithm	**Incident duration**	**DR (%)**	**MTTD (s)**	**FAR (%)**
SVM	Less than 4 min	83.12	82.19	2.1
	Less than 6 min	38.41	39.12	0.40
RF	Less than 4 min	83.78	82.60	2.1
	Less than 6 min	91.87	38.32	0.43
ELM	Less than 4 min	83.84	83.45	2.1
	Less than 6 min	90.98	39.94	0.42
R_ELM	Less than 4 min	85.82	81.66	2.2
	Less than 6 min	91.87	38.95	0.45
PSO_RELM	Less than 4 min	87.65	80.98	2.2
	Less than 6 min	93.78	37.94	0.46

Source: created by the authors.

To assess the effectiveness of our suggested model, we compared the outcomes of PSO-RELM with those obtained from the SVM, RF, R-ELM, and the basic ELM algorithm. The performance comparison centred on training time, accuracy, and estimation capacity, with RMSE as the metric. The RMSE is defined by the following equation, where y_i denotes the predicted value, x_i is the measured value, and is typically used in regression tasks;it is included here to evaluate prediction error in model outputs. Accuracy is also reported for general comparison, although it may be less informative under class imbalance.

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(y_i-x_i)^2}{N}} \quad (23)$$

To further validate the performance improvements of the proposed PSO-RELM model over baseline methods, a statistical significance analysis was conducted. A paired t-test was used to compare results across multiple runs from different models. The results indicate that the observed improvements are statistically significant at a 95% confidence level, confirming the effectiveness of the proposed approach.Thecorresponding performance evaluation metrics and statistical measurements are summarized in Table 2.

Table 2. Performance measurement

Performance	**PSO_RELM**	**R_ELM**	**ELM**	**SVM**	**RF**
RMSE	0.0911	0.0998	0.1012	0.7066	0.8129
Training time(s)	1.1733	1.1987	1.1988	3.0923	4.5032
Accuracy	0.95	0.94	0.93	0.91	0.92
Precision	0.94	0.93	0.92	0.89	0.91
Recall	0.96	0.95	0.93	0.88	0.92
F1-Score	0.95	0.94	0.93	0.88	0.91

Source: created by the authors

Figure 2 shows that our approach achieved higher accuracy ,demonstrating its superior effectiveness in incident detection.

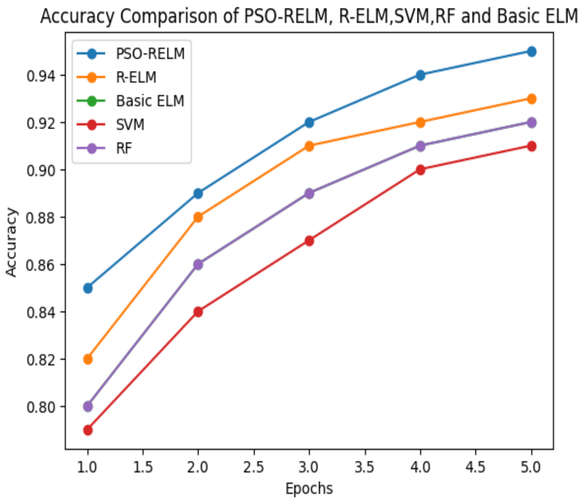

Fig. 2: Accuracy comparison of PSO-RELM, R-ELM, SVM, RF and basic ELM
Source: created by the author

5 Conclusion

This paper proposes hybridizing PSO with the regularized ELM (PSO-RELM) to improve AID on urban roads. The proposed algorithm enables the regularization and optimization of the parameters of the basic ELM, thereby improving the performance, speed, and real-time capabilities of a traffic incident detection model on urban roads. The results indicated that our proposed PSO-RELM model outperformed SVM-, RF-, and ELM-based methods, achieving high detection accuracy.

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