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Development of a Real-Time Video Surveillance System using Enhanced Fuzzy Based Serial Artificial Neural Networks for Transportation Applications

[1]Jitendra Kumar Katariya, [2]Dr. Anand Kopare, [3]Ritesh Kumar, [4]Abhinav Rathour, [5]Kavitha R.

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Abstract: To ensure public safety and security in transportation applications, video surveillance systems are essential. Intelligent surveillance systems with real-time analysis and decision-making capabilities are becoming more and more in demand as a result of the complexity of transportation networks and the necessity for effective monitoring. This study describes creating an advanced real-time video surveillance system for transportation applications that uses an enhanced fuzzy-based serial artificial neural network (EF-SANN). The dataset comprises real-world video footage shot in various transportation-related locations, such as motorways, bus terminals, and traffic crossroads. The video data includes a variety of scenarios, including traffic, people walking, and crowd behavior. Preprocessing using the Z-score normalization is employed to enhance the quality and usability of the dataset. These techniques encompass video stabilization, noise reduction, frame extraction, and object annotation. The preprocessed dataset is the basis for EF-SANN architecture development and evaluation. The system uses serial artificial neural networks and advanced fuzzy logic for object detection, tracking, behavior analysis, and anomaly detection. The studies performed with the dataset show how the EF-SANN approach is effective in accomplishing accurate real-time monitoring goals. The system demonstrates excellent object detection and tracking precision, successfully analyzes object behaviors, and successfully identifies anomalous actions.

Keywords*: Real-time video surveillance system, transportation applications, enhanced fuzzy-based serial artificial neural network (EF-SANN), Z-score normalization, effective monitoring*

1. Introduction

Due to the growing urbanization process, there has been an increase in demand for urban automobiles, and traffic congestion has become a much bigger problem. A development framework made public by the State Council includes big data. Big data's large amount of information serves as an example of its significance. The human brain can analyze enormous volumes of data as a natural data processing engine. Physical tools like radars, infrared detectors, and underground loop sensors can be used to gather traffic data. However, video surveillance cameras have shown to be a very efficient and cost-effective way to monitor traffic. Multiple traffic lanes on various routes can be monitored by a single camera without the need for expert installation and calibration. [1]. In order to address the energy crisis and reduce carbon emissions, it has become increasingly popular to speed up the development and promotion of Electric Vehicles (EVs). Lithium-ion batteries have gained popularity as the preferred option for EV car battery systems due to their advantages of being lightweight, having a low discharge rate, and having a high energy density. However, an unbalanced lithium-ion battery pack connected to the vehicle may result in an internal short-circuit defect brought on by the overcharging of a single battery, further impairing the normal operation of the entire system. Overcharging, which overpowers lithium-ion batteries with energy, is one of the most significant safety issues with these batteries.

Traffic cameras are filling a huge need in today's traffic sensor needs thanks to their advantages of being affordable, information-rich, and extensively used. As a result of recent advancements in computer vision, information technology, and traffic operations, traffic video analytics is powering a wide range of smart city applications that have the potential to significantly improve existing and upcoming transportation and infrastructure systems. For the majority of these applications, such intelligent traffic surveillance and autonomous driving, real-time computing power is also necessary. It is well acknowledged that real-time video

[1]*Department of Computer Science & Application, Vivekananda Global University, Jaipur jitendra.kumar.katariya@vgu.ac.in, Orcid Id- 0009-0000-9940-9022*
[2]*Department of ISME, ATLAS SkillTech University, Mumbai, Maharashtra, India, Email Id- anand.kopare@atlasuniversity.edu.in, Orcid Id- 0000-0003-2948-3192*
[3]*Maharishi University of Information Technology, Lucknow, India - 226036, Email Id- riteshkumar268@gmail.com, Orcid Id- 0009-0008-6351-083X*
[4]*Chitkara University, Rajpura, Punjab, India, abhinav.rathour.orp@chitkara.edu.in, https://orcid.org/0009-0008-4434-1073*
[5]*Jain (Deemed to be University), Bangalore, Karnataka, India, Email Id-kavitha.r@jainuniversity.ac.in, Orcid Id- 0000-0001-6722-9297*

analytics is one of the most difficult yet effective applications for Smart towns. The abundance of video data, the high cost of computation, and the constrained data connection bandwidth frequently cause bottlenecks [2]. Artificial neural networks, which have a high modeling capacity, speed, and capacity to learn how to solve non-linear issues and provide the flexible technical solutions that the industry needs, are one of these techniques that are growing in popularity and interest in a variety of industrial applications. Artificial neural networks can be used to imitate system behavior in numerous industrial systems and manipulate data in a variety of ways. Because they swiftly use data from the monitoring variables, these artificial intelligence systems are extremely effective and precise for decision support [3]. Since reducing the risk of supply chain disruption is a corporate goal, academic research has focused on this topic. Supply chains now take up greater space and have significantly shorter supply cycles due to recent innovations, including cross-border business transactions, non-core business outsourcing, single-source supply, and lean production. Changes in space and time make disruptions more likely. Additionally, supply chains grow increasingly fragile, and the likelihood of a disruption of the supply chain increases as a result of the likelihood that natural disasters, economic fluctuations, diseases, terrorism, conflicts, and other events will occur. One facet of supply chain disruption risk management is the disruption of transportation [4]. Fire accident is one of the biggest threats to the environment, the economy, and human life. Due to the rapid increase in fire incidents, fire protection and fire prevention systems are now present in every building and public transportation passenger vehicle. These systems frequently employ point-type thermal and smoke detectors, which must be placed near the fire for proper operation and fire detection. Due to the fire risk, these devices must also be properly fixed and positioned. Video-based fire detection is already a widely used technology because to image processing, computer vision, and artificial intelligence. These gadgets might perform better regarding response speed and detecting range than other well-known methods [5]. Combining autonomous and manual cars as a component of an Intelligent Transport Systems (ITS) might have unexpected effects on safety, security, and resilience due to their disparate capabilities. Autonomous vehicles, for instance, can electronically interact with other vehicles, make snap decisions, and execute corresponding actions: they often function deterministically. In contrast, manual cars cannot interact electronically, have constrained capacities, and are hampered by the slow reflexes of human drivers; as a result, they may display doubt or even react irrationally. In contrast to autonomous vehicles, people usually react to complex circumstances more properly [6]. Currently, 5G-capable ITS largely employs models and techniques based on machine learning to give end users comfort and safety. Other issues in contemporary ITS, however, such as traffic management, safety and security, and congestion reduction, can be solved using AI-based solutions. According to the research that is currently accessible, deep learning-based techniques are frequently employed in ITS for object recognition, localization, and classification. As a result, driving and using a vehicle are both fantastic. Modern ITS frequently uses Convolutional Neural Networks (CNN) and their derivatives for object identification, localization, and categorization [7]. Mobility is a multidimensional, heterogeneous concept that refers to the movement of both people and goods. The quality of human existence is continuously improved by improvements in mobility, but these improvements also bring about obstacles and drawbacks known as transportation externalities. Traffic congestion is an example of an NP-hard problem; it is brought on by cars, and both speed up and slow down mobility. Transport issues are complex system difficulties due to externalities and NP-hard problems [8]. In many major cities worldwide, the number of cars is continuously and unchecked rising. This tendency causes a variety of problems with how the transportation system is managed, including traffic congestion, environmental damage, and an increase in traffic accidents. To coordinate the continuous flow of traffic across crossings, numerous research teams are developing V2V and V2I systems that enable communication between infrastructure and cars [9]. The visual monitoring of moving objects, such as cars, has been a subject of active research due to the inefficiency of the currently used technique, which involves setting up control towers manned by traffic cops to monitor traffic conditions. This is because there are more roads and traffic cameras, which indicates that it would take more time, physical labor, and effort to watch for incoming traffic on the motorways [10].To address current transportation difficulties, routine and reliable data collecting is needed. When advanced technologies are utilized to collect data, the cost of data collection rises noticeably. State Departments of Transportation struggle to get reliable data for timely analysis and resolution of transportation issues as a result of this restriction. The cost of data collection has decreased as a result of recent developments in smartphone sensors [11]. Road-Side Units (RSUs) and intelligent cars communicate with one another in these systems over the VANET. The level of urbanization, size, and spatial design of a city all have an impact on how congested its streets are. Both our daily journey and the focus of ITS now include traffic monitoring. ITS gathers traffic information to offer vehicle classification, vehicle density, vehicle path, and vehicle speed. [12]. Determining the mode of movement has evolved into a relevant application in an intelligent transportation system because it offers context-aware support for the development of systems like driver assistance and intelligent transportation management. Law enforcement officers, traffic controllers, and toll collectors may utilize this data to control traffic flow, lessen congestion, and improve safety [13]. The study [14], a heuristic artificial neural network model was used to predict how non-autonomous cars will move. ITS attack traffic and malicious node identification are actively being studied.. Our civilization is enriched by more intelligent technologies that enable us to carry out our daily tasks more effectively and efficiently as technology continues to advance. One of the most significant technological advancements of our day is the Internet of Things (IoT), which connects a variety of smart gadgets to enable easy data sharing. The research also attempts to look into the information flow in smart cities related to ICT [15]. Additionally, the research defines the geographic similarity of training images for sports and provides a local linear weighting approach for analysis in a CNN's fully connected layer. The study [16] employed the multi-evaluation standard fusion approach to select the suspicious region feature and gives each prediction point near the area that needs to be forecasted a certain weight. Due to urbanization's rapid development, existing parking facilities are currently unable to satisfy the growing demand for parking. Video-based parking surveillance equipment is the most popular method for giving real-time parking information as the essential data feed for a parking management system. It contains a plethora of information, is easy to deploy, and has powerful algorithms [17]. Auto accidents are more likely to result in serious injuries and fatalities. There are numerous other ongoing issues with it as well, such as the frequent loss of life and property in accidents. Appropriate steps must be taken to address these problems, like setting up an autonomous event detection system that utilizes machine learning and artificial intelligence [18]. The study [19] provided an overview of artificial intelligence and machine learning in autonomous event detection systems in an effort to reduce traffic accidents. In order to decrease traffic accidents, the article examines the key problems, potential fixes, and applications of artificial intelligence and machine learning in road transportation systems . CNN are promising and fascinating for vehicle identification and classification in intelligent transportation systems. Large-scale labeled vehicle photos, which are uncommon in settings in developing countries, are typically used to train CNN. The research suggests a CNN-based vehicle detection method that doesn't need a labeled vehicle dataset. Road markings are used as the background when a CNN is trained. Logic 1 is saved in the database when a car park at a road marks; otherwise, logic 0 is saved. The occupancy data collected provides spatiotemporal information that may be used to measure and categorize the width and length of vehicles. A GPU is not necessary for training or real-time implementation of the approach [20]. This study discusses the creation of a real-time video surveillance system for transportation applications using enhanced Fuzzy-based Serial Artificial Neural Networks (EF-SANN).

2. Methodology

This section covers the creation of an Enhanced Fuzzy based Serial Artificial Neural Networks based real-time video surveillance system. Fig.1 shows the structure of the proposed method.

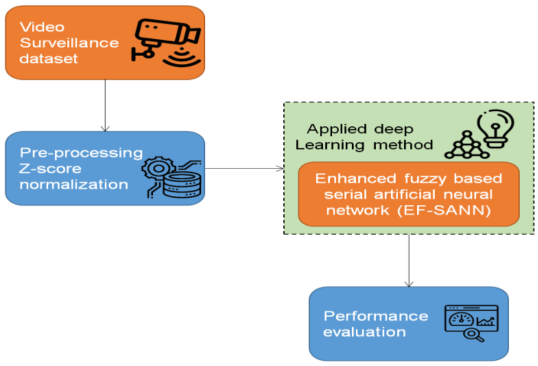

Fig.1. Structure of Proposed Method

2.1 Unmanned aerial vehicles (UAVs) and Traffic Monitoring

The Department of Transportation (DOT) and numerous other organizations are interested in real-time highway traffic monitoring. Monitoring traffic emergencies, particularly to provide emergency services, and obtaining data that would help the DOT improve the highways are the more important objectives of implementing traffic surveillance. Currently, magnetic loop detectors placed beneath highways are used to monitor traffic. These loop detectors are only used to count traffic. To handle real-time traffic surveillance and analysis across highways, cutting-edge video monitoring systems and research methodologies, such as IBM's Real-time Video Traffic Surveillance and UC Berkeley's Machine Vision Based Traffic Surveillance, are being developed. A challenge is delivering the footage to the organization in charge of the surveillance. This issue can be solved by using manned or unmanned aircraft, tower-mounted cameras next to the highways, or both. The cost and duration required for equipment setup contribute to the challenge of installing cameras on roadways. Remote installations would be extremely expensive. One disadvantage of man-made airplanes is their exorbitant price. UAVs are a superior option in this situation.

2.2 A Passion for Traffic Surveillance

The Department of Transportation recognizes the usefulness of traffic monitoring. Several ideas were taken into consideration in order to develop a system that would allow traffic surveillance to advance in the future, but unhappily, most of them were unfeasible. Using manual aircraft and cameras, for instance, would be very costly and time-consuming, as was previously mentioned.

2.3 Video Surveillance dataset

Cameras are used in a system called video surveillance, commonly referred to as closed-circuit television (CCTV), to observe and document activity in a particular space. It is frequently employed for security and surveillance reasons in a range of contexts, including public places, commercial establishments, residential neighborhoods, and transportation networks. For our studies, we created a dataset of 400 images of the fire and smoked to train the YOLOv2 detector. The Kaggle website was used to collect the photographs. These pictures were chosen from a variety of open fire and smoke disaster scenarios. The MATLAB images were labeled using a ground truth technique. (https://www.kaggle.com/datasets/ashutosh69/fire-and-smoke-dataset).

2.4 Preprocessing using Z-Score Normalization

Z-score normalization, commonly referred to as standardization, is a statistical method for changing a dataset's mean and standard deviation to zero and one, respectively. Each data point is taken, the dataset's mean is subtracted, and the result is divided by the dataset's standard deviation. The consumers may comprehend where a certain rating might fit into a typical regular set of facts with Z-score normalization. Z-Score is carried out to manage outliers in a collection**.** The converted dataset will have a mean of zero and a standard deviation of one when Z-score normalization is applied. This normalization technique is frequently used to compare and analyze data that may have different sizes or distributions in a variety of domains, including statistics, data analysis, and machine learning. All variables are helped to be placed on a similar scale, which makes them easier to compare directly and more appropriate for some modeling or statistical tasks.

$$\underline{z} = \frac{z-\tau}{\varsigma} \quad (1)$$

Z stands for the quantitative component and z¯is the freshly assumed data point, τ indicates the mean of the data points, and ς indicates the variance of the data points.

2.5 Enhanced Fuzzy based Serial Artificial Neural Network (EF-SANN)

In order to tackle difficult issues and enhance decision-making, the Enhanced Fuzzy based Serial Artificial Neural Network (EF-SANN) is a sophisticated computational framework that combines the advantages of fuzzy logic and Artificial Neural Networks (ANNs). It represents a development in intelligent systems, providing improved data analysis, pattern recognition, and decision support capabilities. The EF-SANN architecture uses linguistic variables and fuzzy rules to take use of the fuzzy logic system's capacity to handle ambiguous and imperfect input. Fuzzy logic is appropriate for applications where precise mathematical models are not available or practical because it allows for the representation of vagueness and ambiguity in data.

Artificial neural networks, which are renowned for their capacity to learn from data and produce predictions or classifications based on patterns and examples, are also incorporated into the EF-SANN. ANNs are excellent at identifying intricate patterns and correlations, and their parallel processing capabilities enable speedy calculations. The EF-SANN's "serial" component refers to the sequential organisation of the neural network layers, where the output of one layer serves as the input for the subsequent layer. This architecture makes it easier for data to move throughout the network, allowing for efficient data processing and feature extraction. The EF-SANN's improved capabilities make it especially well-suited for use in a variety of areas, including transportation. The EF-SANN has applications in real-time video surveillance, traffic flow optimisation, anomaly detection, and decision support in the context of transportation systems.

EF-SANNs have been effectively utilized to model a range of different functions since the late 1980s. Through an autonomous training procedure, the network may intelligently learn these functions. Many network architecture-related concerns, however, are still not well understood. According to several academics, EF-SANNs are a "black box" method that cannot offer significant and practical insights into the underlying nature of the physical processes. An EF-SANN attempts to mimic the functionality and structure of the human mind and brain in a very crude manner. It can be characterized as a system made up of a network of interconnected basic neurons. Numerous nodes are joined via links that are usually layered multiple times to form the network structure. Links are utilized to transmit each node's output to nodes in the upper layer after each node in a layer processes weighted input from a lower layer. Each link is assigned a weight, which represents a quantitative evaluation of the connection's strength. A transfer function converts the weighted sum of an input at a node into an output.There are three equations that characterize the back-propagation algorithm. In each learning step k, weight connections are first altered.

$$\Delta V_{ij(k)}^{s} = \eta(t)\delta^{s}pj^{ui^{(s-1)}} + m\Delta V_{ij(k-1)}^{s} \quad (2)$$

Second, the information below is correct for output nodes:

$$\delta_{pj}^{o} = \left(d_j - o_j\right) f'\left(I_j^s\right) \quad (3)$$

and thirdly, it is true for the other nodes.

$$\delta_{pj}^{o} = f_j\left(I_j^s\right) \Sigma_k \quad f'\left(I_j^s\right) \quad (4)$$

Where $u_j^{(s)}$ is the actual results of node$j$in layer$S$; $V_{jk}^{(s)}$is the weight of the connection between node$j$at layer$(s-1)$and node$j$at layer$I$; $V_{jk}^{(s)}$is the measure for the actual error of node$I$; $I_{(s)}^{(s)}$is weighted.

3. Results and Discussion

A method's reliability and efficacy are compared to those of more established methods like Convolutional Neural Networks [21] and Deep Neural Networks (DNN) [22] to show how effective it is. It has been recommended that ANN be used in the real-time video surveillance system. These approaches are compared to conventional methods based on a variety of parameters, including accuracy, precision, recall, and implementation cost.

3.1 Accuracy

Accuracy is defined as the capacity to classify an incident properly based on its overall frequency in a real-time video surveillance system. Fig.2 displays the accuracy of the present and future systems. Because of its precision, it has been suggested that the proposed EF-SANN be utilized to create a real-time video surveillance system. While CNN and DNN have accuracy levels of 93.5% and 94%, respectively, the suggested method has a 98% accuracy level. It demonstrates that the suggested method is more accurate than the current one. Table 1 shows the accuracy values.

$$Accuracy \rightarrow \frac{TP+TN}{TP+FP+FN+TN} \quad (5)$$

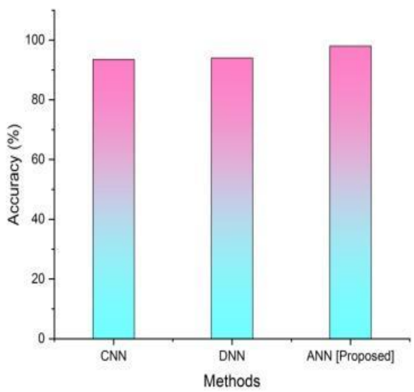

Fig.2. Accuracy for existing and proposed method

Table 1: Comparison of accuracy

Methods	Accuracy (%)
CNN	93.5
DNN	94
ANN [Proposed]	98

3.2 Precision

A classification model's capacity to isolate only the pertinent data points is used in the development of a real-time video surveillance system. The precision of the proposed and current systems is shown in Fig.3. It has been recommended that the proposed EF-SANN s' accuracy be used for transportation applications. CNN has attained 94.6%, and DNN has achieved 96.4%, whereas the proposed system reaches 97.2% of precision. It shows that the proposed approach has more precision than the existing one. Table 2 depicts the values of precision.

$$Precision \rightarrow \frac{TP}{TP+FP} \quad (6)$$

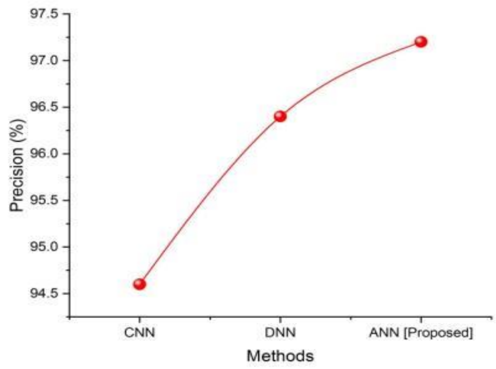

Fig.3. Precision for existing and proposed method

Table 2: Comparison of precision

Methods	Precision (%)
CNN	94.6
DNN	96.4
ANN [Proposed]	97.2

3.3 Recall

The recall is calculated mathematically as the total of true positives less false negatives. The ability of a model to find all pertinent events in a batch of data can be used to create a real-time video surveillance system. Fig.4 depicts the planned and current systems' recalls. It has been recommended to use the projected EF-SANN recall in transportation applications. CNN has attained 91.1%, and DNN has achieved 95.2%, whereas the proposed system reaches 96% of recall. It shows that the proposed approach has more recall than the existing one. Table 3 depicts the values of recall.

$$Recall \rightarrow \frac{TP}{TP+FN} \tag{7}$$

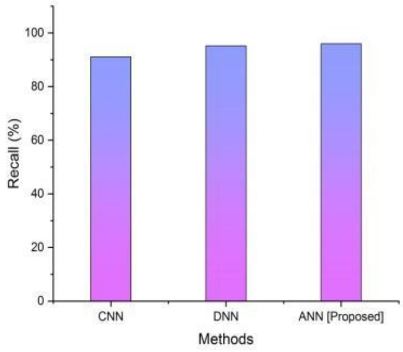

Fig.4. Recall for existing and proposed method

Table 3: Comparison of recall

Methods	Recall (%)
CNN	91.1
DNN	95.2
ANN [Proposed]	96

3.4 F1-Measure

The F1 measure is a statistic that evaluates the overall effectiveness of a classification model or system by combining accuracy and recall. It is frequently employed to evaluate how well a model does in correctly identifying and classifying transportation applications. The F1 measure for the proposed and existing systems is shown in Fig.5. It has been recommended to use the measure of the proposed EF-SANN in transportation applications. The suggested system achieves 93.6% of the F1 measure, whereas CNN has obtained 88.3% and DNN has attained 91.2%. It demonstrates that the recommended strategy has a higher F1 measure than the existing one. The F1-measure values are shown in Table 4.The F1 measure is the harmonic mean of recall and accuracy, which adds the two metrics to get a single value. It is computed using the following formula:

$$F1 - Measure \rightarrow 2 * \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{8}$$

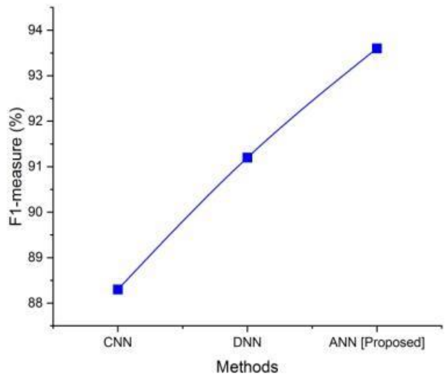

Fig.5. F1-Measure for existing and proposed method

Table 4: Comparison of f1-measure

Methods	F1-measure (%)
CNN	88.3
DNN	91.2
ANN [Proposed]	93.6

4. Conclusions

In conclusion, the creation of a real-time video surveillance system for use in transportation applications that uses EF-SANN is a significant step forward in assuring the security and effectiveness of transportation systems. The use of EF-SANN improves the system's capacity to recognise and categorise numerous objects and events in real-time video streams by combining the strengths of fuzzy logic and artificial neural networks. Our video security surveillance system provides a precise and real-time car count for important routes using readily available stationary web cameras. The visual analyzer processes the traffic videos for output in detection, analysis, and visualization. Future research holds significant promise for the creation of real-time video surveillance systems using improved EF-SANN for transportation applications. EF-SANN can result in better object detection and event recognition in video surveillance systems [23]. Systems for real-time surveillance can profit from powerful object tracking and behavior analysis tools. In the future, improved tracking algorithms and machine learning methods may be combined to precisely follow objects of interest, forecast their behavior, and spot abnormalities or potential hazards. An important step towards improving security, effectiveness, and overall safety in transportation systems is the creation of a real-time video surveillance system using EF-SANN for transportation applications. The system has the potential to revolutionise video surveillance in the transportation industry and aid in the development of smarter, more secure transportation networks thanks to its capacity for handling complicated situations, adapting to uncertainties, and issuing prompt alarms.

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