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An approach in using Artificial Intelligence for traffic light optimization (fuzzy method)

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Abstract

Optimization of traffic light has been a hotspot for years, because of technology advancement for the latest 20 years, high demand in international market for car companies to develop, produce more cars and also geographic conditions, high standardatization of live enhance this problem. In this paper I will use an approach in traffic light optimization by using machine learrning technique, to train a set of data, in order to compute and produce best solutions for optimization of traffic light. There have been many methods used such Webster method, Pedri Net algorithm model, fuzzy model and so on. I will use a different approach to fuzzy method, with intention to provide better output result, decrease the amount of released gases in atmosphere, lower delay and waiting time of cars in a traffic jam. In metropol cities consisting million of people where urban infrastructure is complex, only the development and improvement of these methods can make people's live more simple. One of most early algorithms to minimize cost in travelling through one or lots of routes is Djikstras algorithm, where simultaneous tests to use different routes, chose the best route, thus minimizing consumption and increasing output efficiency. The paper will be divided into several sections: Introduction, where a set of definitions, general terms of traffic light software simulation are presented, Big Data, representing the dataset of input where in Artificial Intelligence are the building 'bricks' into comparing and anlazying the ouptut results of different methods/algorithms (Pedri Net algorithm, fuzzy model, improved RNN Djikstra Algorithm etc.). The upcoming section Methodology, gives a general idea of into analyzing Webster's algorithm and breaking it down into smaller parts, The Derivation of Fuzzy Method, when analyzing bits of components, methodology used in traffic light system and proposed smart system nowadays, fuzzy method is one of the roots in considering clustering techniques, VANet System Architecture, in this section a proposed system architecture is used, it is one of the most importants sections because it approaches a solution, which is a derived form of Internet of Thing (IoT) components into achieving a Smart City System, Result section gives output where in the upcoming sections can be used as proposals and ideas. Neural Network, CNN (Convolution Neural Network), DL (Deep Learning) and RNN (Recurrent Neural Network) are sections dedicated to relation between artificial intelligense and smart city implementation, where the main idea is training large amounts of datasets to propose smart, efficient and reliable solutions. In conlusion and future work section, the proposed solutions underline the importance of correlation between general methods: Fuzzy, Webster method with big datasets (machine learning techniques) and future work ideas highlight the necessity of virtualization and doubling – quadrupling the layers of CNN, which is proportional to hardware computational cost.

Keywords

Machine learning; fuzzy method; optimal control; microcontrollers; ReLu; deep learning

Introduction

A large amount of car production and their high demand in usage on urban roads in larger cities where the population boosts year after year requires new urban models in road intersection, while congestion relieving is estimated to be 3-4 times higher than before. (Zhang H., 2021). Traffic congestion is one of the most prevalent problems on the streets in urban areas, especially at intersections that are not properly controlled, so it causes problems in the flow of traffic and the disruption of the streets. Many new solutions has been proposed. A new solution proposes an intelligent control system, which uses a traffic light method called Dynamic Webster with Dynamic Cycle Time, which runs by software simulation (P.A.Sumayya, 2014).The optimization of traffic light is derived from Green Wave. A Green Wave occurs when a series of traffic lights (usually three or more) are coordinated to allow continuous traffic flow over several intersections in one main direction. Any vehicle travelling along with the green wave (at an approximate speed decided upon by the traffic engineers) will see a progressive cascade of green lights, and not have to stop at intersections. This allows higher traffic loads, and reduces noise and energy use. According to a study which modeled the implementation of green waves using SParamics microsimulation and the AIRE emissions module, (Mascia M. H., 2017) the results below were shown which in fact they were significant to what advantages it could bring to us.

- reduce CO2, NOx and PM10 emissions from traffic;
- reduce fuel consumption of vehicles;
- be used on roads that intersect with other green waves.
- reduce the time cars wait at side roads;
- give pedestrians more time to cross at crossings and help- them to cross streets as vehicles travel in platoons;
- control the speed of traffic in urban areas;

With the introduction of AI, by training big data and usage of stationary and GPS sensor, now it is possible to develop "smart" models to forecast traffic congestion. This is achieved by acquiring historical data, thus giving results under different methods used, summarising strengthness, reliability and weakness of each method.

Big data

Based on extensive research and analysis conducted, it is evident that the traffic datasets utilized in various studies can be classified into two primary categories, namely stationary and probe data. The stationary data category can be further delineated into sensor data and fixed cameras (Akhtar, 2021), whereas the probe data encompasses GPS data affixed to vehicles, serving as a critical component in the studies. It is notable that stationary sensors play a vital role in continuously capturing spatiotemporal traffic data. However, it is imperative to acknowledge the possibility of interruptions in sensor operation, which can potentially affect the data's reliability. Consequently, authorities and stakeholders are advised to account for these temporary sensor failures during the planning and utilization of such data. It is worth emphasizing that the use of sensor data offers the distinct advantage of providing precise vehicle location information, thereby minimizing any potential confusion or ambiguity in the dataset. There are lots of datasets, where the most used one is Performance Measurement System (PeMS) (Chen, 2002). Through meticulous research and comprehensive analysis, it has become apparent that probe data offers a notable advantage in its capacity to encompass the entirety of the road network. Given the diverse nature of road infrastructure within a network, studies focusing on a broad network scope have demonstrated a preference for utilizing probe data. Notably, one of the frequently employed datasets comprises GPS data, collected at one-second intervals from an extensive fleet of approximately 20,000 taxis in Beijing, China. This dataset encompasses critical parameters such as taxi identification numbers, latitude-longitude coordinates of each vehicle, corresponding timestamps, and the occupancy status of the taxis during sampling periods. It is imperative to note that the data updating frequency for this specific dataset ranges from 10 seconds to 5 minutes, contingent upon the quality of the integrated GPS devices. Furthermore, it is worth acknowledging that non-intrusive tracking of cellular phone movements can serve as an additional data source, ensuring privacy preservation. However, it is essential to recognize that determining the heterogeneous distribution of vehicles from this dataset might prove challenging, if not infeasible. Additionally, when conducting modeling for a road network, the presence of outliers within the dataset may arise due to pedestrian or cyclist movement alongside the roadways. The database which I will use in my publication derives from one of too many prediction datasets in ***https://www.kaggle.com/***. From the data interpretation I will employ the usage of fuzzy method, with small altering changes to give actual and reliable results.

Derivation of Fuzzy-C algorithm

In the realm of data mining, Fuzzy C-Means (FCM) has emerged as a prominent non-deterministic clustering technique. Within the domain of traffic engineering research, the recognition of traffic patterns assumes a pivotal role. These research endeavors often encounter challenges stemming from the presence of incomplete or missing data. In response to these constraints, FCM has garnered widespread application as a preferred clustering technique. Notably, this approach offers a distinct advantage over the original C-means clustering methods by effectively mitigating the issue of convergence to local optima. However, it is important to highlight that the utilization of FCM necessitates the establishment of a predefined cluster number, a requirement that may not always be feasible when handling substantial datasets lacking prior insights into the data dimension. Moreover, the computational complexity of this model escalates with an increase in data size, potentially posing challenges in practical applications. Diverse studies have demonstrated successful applications of FCM by addressing and enhancing its inherent limitations, thereby showcasing its adaptability and efficacy in accommodating complex data scenarios.

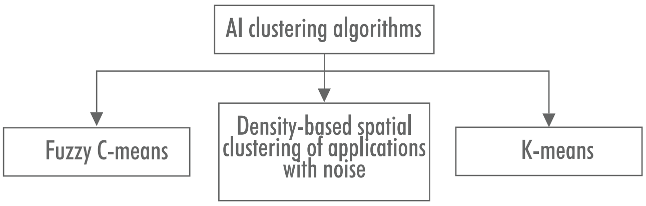

Figure 1: . AI used methods.

Methodology

Traffic congestion is one of the most prevalent problems on the streets in urban areas, especially at intersections that are not properly controlled, so it causes problems in the flow of traffic and the disruption of the streets. Many new solutions has been proposed. A new solution proposes an intelligent control system, which uses a traffic light method called Dynamic Webster with Dynamic Cycle Time, which runs by software simulation. Webster's method for traffic light design is an ***analytical approach*** of determining several terms which are exploited as below:

Webster's Optimum Cycle determines the optimal time shared in a traffic light system between two or four lanes. It carries out the below formula:

$$C_0 = \frac{1.5 \times L + 5}{1 - \sum_i^n \quad Y}$$

C_0 : optimum length cycle
L : total lost time (when led is yellow)
$\sum_i^n$: total critical volume/saturation flow

$$g_t = C_o - L$$

g_t: total green time

$$g_{i=} \frac{Y_i}{\sum_i^n \quad Y} g_t$$

g_i: effective green time per one phase

Algorithm script:The below representation shows the algorithm logic behind the computations.

start
Input total lost time (L) and total critical volume/saturation flow $\sum_i^n Y$
Calculate C_0*:*
- Multiply L by 1.5 and add 5
- Divide the result by the subtraction of 1 and the total critical volume/saturation flow $\sum_i^n Y$
- Store the result in C_0*:*

Calculate g_t
- Subtract L from C_0*:*
- Store the result in g_t

For each phase 'i' from 1 to 'n':
Calculate g_i
- Divide each Y_i by the total critical volume/saturation flow $(\sum_i^n Y)$
- Multiply the result by g_t
- Store the result in g_i
end

The signal design process encompasses six key steps, which include:

• Phase design,
• Determining amber and clearance times,
• Establishing cycle length,
• Allocating green time,
• Addressing pedestrian crossing needs, and
• Evaluating the performance of the design obtained in the preceding steps.

Phase design aims to segregate conflicting movements at an intersection into different phases to eliminate conflicts. If complete separation without conflicts is sought, a high number of phases may be necessary. In such cases, the goal is to create phases with minimal or less severe conflicts. The development of phases lacks a precise methodology and is often influenced by intersection geometry, flow patterns (especially turning movements), and the relative magnitudes of flow. As a result, a trial-and-error approach is commonly employed. Despite its somewhat subjective nature, phase design holds significance as it sets the foundation for subsequent design steps. Additionally, it is relatively easier to adjust cycle and green times in response to changes in flow patterns, while a drastic shift in flow patterns could lead to significant driver confusion.

VANET (Vehicular Ad-Hoc Network) Smart System Implementation

While discussing about implementation and usage of a smart city, one might suggest VANet "smart" architecture proposal. In the designed VANet system alerting, reporting the surrounding components, thus extending the optimization and reliability of emergency feedback.

Proposed System Architecture

The system comprises several key components: the On-Board Unit (OBU) situated within the vehicle, a dedicated android app named installed on smartphones, a server with a hosted database and a web application, and Road Side Units (RSUs) strategically placed at intersections. The OBU serves to collect data from various sensors within the vehicle, while the RSUs control traffic signals at road intersections. The android app, is integrated into a navigation system, allowing users to access road maps, current location, and route information through a user-friendly interface. Notably, pedestrians with smartphones equipped with can report accidents or road hazards to authorities instantly, triggering emergency services without legal complications. For users driving vehicles, the OBU automatically detects accidents and reports them to the relevant authorities. Bluetooth technology facilitates communication between the OBU and the smartphone, while RF transceivers establish communication between RSUs.

In response to events such as accidents, medical emergencies, breakdowns, or congestion, the smartphone sends messages to the main server, providing relevant data and the vehicle's location. The server maintains real-time tracking of each vehicle and traffic data, communicating with individual vehicles to facilitate necessary services. The network diagram depicted as below, illustrates the interactions between system components, each serving specific functions:

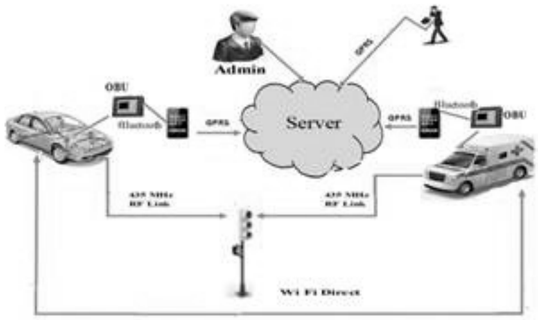

Figure 2: Network diagram (proposed system architecture)

• ***OBU***: Responsible for acquiring and collecting sensed data from vehicle sensors.
• ***RSU***: Manages and controls traffic signals at intersections.
• ***Hosted database***: Stores user accounts, vehicle details, hospital information, and emergency vehicle details.
• ***Web application***: Includes a website for user and hospital registration management and an HTTP service to handle requests between mobile clients and the database server.
• ***Android application***: Acts as the client interface for users participating in the system.

Results

The results taken from the application of the above algorithm, simulated in a test network in Glasgow examining the impact of three traffic management measures: traffic signal control (TSC), variable message sign (VMS), and a combination of both. To address daily traffic variability, five different demand levels were considered. The results revealed that these interventions effectively reduced BC emissions and enhanced traffic conditions, but their effectiveness depended on factors such as demand levels and VMS compliance rates. Regarding demand levels, the study initially explored five boundary conditions, demonstrating varied impacts. However, to provide more comprehensive insights into the benefits of these interventions, a more detailed examination with finer variations in demand is recommended. The VMS compliance rate was treated as an exogenous variable in the study. To enhance accuracy in estimating the impact of ITS actions, future research should consider modeling the compliance rate as an endogenous variable (Mascia M. H., 2017), allowing for a more in-depth analysis of its interaction with traffic flows across the network. An in-depth analysis of BC emissions per vehicle type highlighted the significant contribution of buses to overall emissions. Even a low bus flow, equivalent to 5% of the total flow (17 vehicles per hour), was found to be responsible for 71% of the overall BC emissions on the link. This suggests that interventions targeting specific vehicle types may be more effective in reducing BC emissions compared to the studied ITS actions.

Neural Network

The comprised methods of CNN in image segmentation, may alter from each-other in spite of dimensions size input, network depth, filter size, input size etc. Several methods were proposed for image segmentation like: Deep-Medic, FCN-8 and all of these methods had the same root architecture U-Net. It has been proved that CPU core can compute around 6 billion floating points operations. Compared to an average human brain this amount of computation is likely unimaginable to be processed, even though there are no records of 100% power exploiting of human brain. Unlikely to traditional CPU-s human brain is able of computing lots of tasks per fraction of time for instance classification of images. That is the reason why even in the beginning of DNN development in 40s, researchers tried to imitate human brain, where this concept was called as Artificial Neural Network

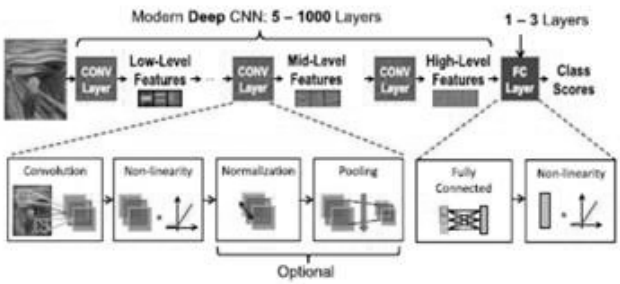

Figure 3: CNN (convolution neural network)

Each of the convolution layers of the CNNs produce a high level of abstraction name f-map (feature map), which conserves essential information. Nowadays, CNNs are able to perform in high level, while introducing a hierarchy layer. After the convolution of the CNN layers the input activators are structure in 2-dimension feature maps, called channel. Every channel is comprised of filter sets, unique for each and every channel, where many times this filter set is denoted as a 3-D filter. Therefore, the convolution products for every point are added together, where the result of the computation output is nonetheless but activation output, named output feature map. Moreover, all input feature maps are processed together as a batch (Yang, 2023), resulting in improvement of filter weights. Additionally, there are other optional layers, as observed in the figure above like, nonlinearity (generally it can evaluate the maximum value of two intersecting function), pooling (it makes the network to withstand to any invariance or distortion) and normalization which is nonetheless but, controlling the input distribution through the layers. Its formula is as below:

$$y = \frac{x - \mu}{\sqrt{\sigma^2 + \varepsilon}} + \beta$$

- y, β: parameters
- Ɛ: small constant

In convolution neural network the processes occur as below:

Firstly, when the images arrive the computer is to much literal and unable to decide, therefore ConvNets (convolution neural network) matches all the pieces of the image, then filtering happens later on pooling (max pooling), normalization, ReLu, (rectified linear unit) fully connected layer then learning.

The realm of deep learning, a subset of machine learning methodologies employed for data feature extraction, has prominently utilized Convolutional Neural Networks (CNNs). CNNs, a specialized form of artificial neural networks that have been expanded across spatial dimensions through shared weights, have demonstrated their efficacy in various computer vision tasks. Initially, researchers conducted experiments with relatively modest datasets. However, with the reduction in costs associated with high-performance processing hardware, the augmentation of chip processing capabilities, and the exponential growth of online data repositories, the application of deep neural networks has expanded to encompass larger datasets and real-world scenario-based datasets.

One particular CNN (convolution neural network) model, the AlexNet introduced by Krizhevsky in 2012 (Krizhevsky, 2012), has garnered significant attention and adoption within the computer vision research community. This adoption stands as a testament to the substantial advancements in leveraging deep learning frameworks for addressing intricate computer vision challenges. (Nishani E., 2017, June).

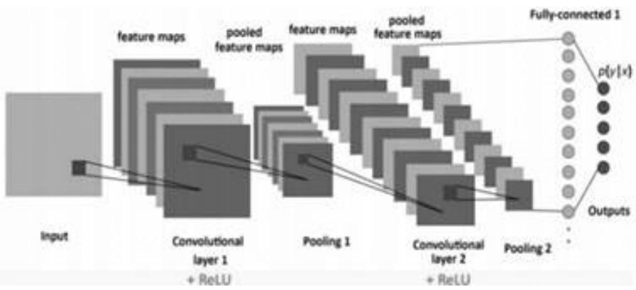

Figure 4: CNN containing 2 convolution layers, 2 pooling layers, and a fully connected

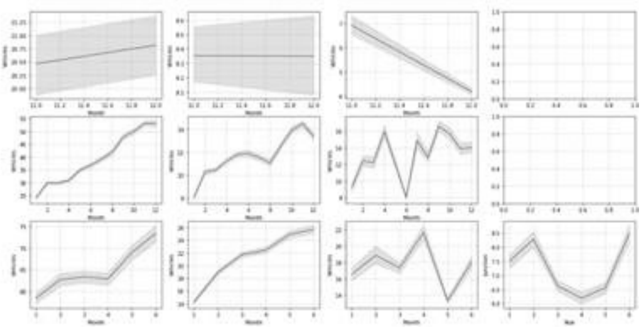

Figure 5: Line plot showing the pattern amounts of vehicles per year after simulating dataset

Efficient traffic light control and the management of urban traffic represent crucial components in the administration of city traffic systems. In this context, our research introduces a novel genetic scheduling model for traffic light control, integrating a status update feature specifically designed for the customization of road signs. This model demonstrates the capacity to dynamically enhance the signal cycle at various intersections, ensuring a remarkably adaptable and responsive approach. Utilizing inputs from camera images positioned strategically along the roadway, our proposed fuzzy logic controller effectively regulates traffic light operations, a feature further supported by the well-documented probability distribution illustrating the flexibility of the fuzzy logic system, thus yielding promising outcomes in simulations (Khazukov, 2020). This controller model enables the implementation of tailored green timing sequences, contingent upon the vehicular density at each intersection. Consequently, it ensures that vehicles do not experience prolonged waiting times, a distinct advantage over fixed-time controllers, as our system adjusts the green signal duration in direct response to the prevailing traffic congestion. This capability underscores the significant impact of traffic conditions on the performance of the Fuzzy Logic Signal Controller (FLSC), with the empirical evidence suggesting notable improvements in traffic flow within various urban settings. Future iterations of this system aim to leverage diverse datasets sourced from multiple cities and locations, incorporating a tracking stage to anticipate traffic conditions before vehicles reach the traffic lights. Our research addresses the challenges associated with the acquisition of data related to vehicle speed and direction from video streams captured by street surveillance cameras, attributed to factors such as varying viewing angles, distance from the intersection, and object overlap.

Fuzzy Method in CNN (Convolution Neural Network)

Furthermore, an additional branch within the YOLO v3 neural network architecture has been introduced, optimizing anchor shapes to enhance object detection and classification precision, particularly for objects of varying sizes. Real-time speed determination employs a method centered on the application of perspective transformation, translating vehicle coordinates within the image to geographic coordinates. In related studies, the integration of fuzzy logic, K-Nearest Neighbors (KNN), and image processing has demonstrated promising potential for identifying vehicular congestion. By employing this approach, the classification of vehicles based on their spatial occupancy becomes feasible, with a particular focus on three primary vehicle types: buses, cars, and bikes. Employing MATLAB (proprietary multi-paradigm programming language and numeric computing environment) algorithms for image processing and vehicle classification, we extract pertinent features such as area, subsequently utilized in the application of fuzzy logic rules. These rules encompass various congestion levels, ranging from light to heavy congestion, quantified as a percentage. Our study underscores the efficacy of incorporating KNN, fuzzy logic, and image processing as a robust strategy for assessing vehicular congestion, offering valuable insights into the optimization of traffic management systems (Chabchoub, 2021).

Deep Machine Learning

Deep learning algorithms (DML) comprise multiple concealed layers aimed at addressing nonlinear problems. A notable advantage of these algorithms lies in their capability to extract features from input data autonomously, devoid of any prerequisite knowledge. Unlike shallow machine learning (SML) techniques, DML integrates feature extraction and model training simultaneously. This characteristic enables DML to effectively transform extensive and intricate traffic datasets, collected within constrained timeframes, into discernible patterns or feature vectors. Notably, in recent years, the adoption of DML (deep machine learning technique) has gained prominence within studies focusing on the prediction of traffic congestion. Figure 8 provides an overview of the traffic congestion studies that have implemented DML algorithms, with detailed discussions presented in this specific section. This integration of DML methodologies in traffic analysis showcases the promising potential of deep learning frameworks in comprehending and addressing complex traffic dynamics.

Recurrent Neural Network

Recurrent Neural Networks are often used to pre-process data like: videos, simple text, different speeches, in that instantaneous position or time depending respectively in the prior data. At each time-stamp the model collects the input from the current time Xi and the hidden state from the previous step hi-1, and outputs a target value and a new hidden state. It exists a type of RNNs called LSTM (long short-term memory) which avoids the issues such are gradient vanishing or exploding problems. (Y. S. L. C. Chao Liu, 2015) LSTM architecture includes gates (input gate, output gate, forget gate), which regulate the flow of information into and out from a memory cell, which stores values over arbitrary time intervals. Furthermore, Recurrent Neural Network can pattern a sequence of data, where every template it is related with the prior model. The perfect process sustainable for the RNN is by convolving every layer, thus increasing effectiveness of the upcoming pixel.

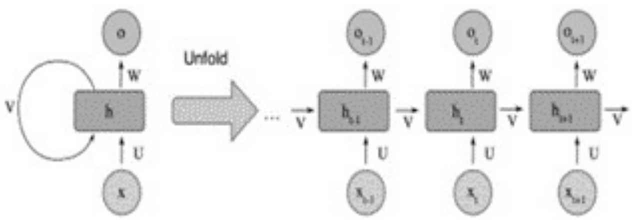

Figure 6: Recurrent Neural Network methodology

In the realms of artificial intelligence (AI), machine learning, and deep learning, neural networks serve to replicate the intricate workings of the human brain, enabling computer programs to identify patterns and address common challenges. Among these networks, recurrent neural networks (RNNs) play a significant role in modeling sequence data. Formed from feedforward networks, RNNs exhibit behaviors akin to those of the human brain. Essentially, recurrent neural networks possess the unique ability to anticipate sequential data, a task that remains elusive for many other algorithms.

While conventional neural networks treat inputs and outputs as independent entities, certain scenarios, such as predicting the subsequent word in a sentence, necessitate the consideration of preceding words. Consequently, the development of RNNs ensued, employing a Hidden Layer to surmount this predicament. Central to the architecture of RNNs is the Hidden state, which retains specific information pertaining to a sequence (Y. S. L. C. Chao Liu, 2015). RNNs boast a Memory function that stores comprehensive information about computations. It applies identical parameters to each input, ensuring that the same task yields consistent outcomes across all inputs and hidden layers.

State of Art – Research Gap

In traffic congestion probability and statistics play an important role in determining and predicting the results. Based on comprehensive investigations and thorough assessments, it has been observed that probabilistic reasoning algorithms were predominantly employed in specific segments of the prediction model, such as for tasks like map matching and optimal feature number selection. Notably, within this category of algorithms, fuzzy logic emerged as the widely adopted approach. Moreover, from related branches, artificial neural networks (ANN) and recurrent neural networks (RNN) (Carbonneau, 2009) were among the frequently utilized models. While several studies employed hybrid or ensembled models falling within the probabilistic and shallow learning class, only a limited number of studies applied hybrid deep learning models for the prediction of network-wide congestion. Detailed information outlining the advantages and limitations of algorithms from different branches can be found in below figure.

Both convolution neural network and recurrent neural network associated together have their own advantages and setbacks, where in different situations different models offer a variety of output results. Among various deep machine learning (DML) models, it was determined that RNN exhibits more suitability for time series prediction tasks. Several studies indicated that RNN outperformed convolutional neural networks (CNN) in scenarios where the disparity between traffic speeds in different classes was minimal. However, given the relative scarcity of research in the traffic congestion domain, there remains a significant potential for the application of new machine learning (ML) algorithms (Patnaik, 2019).

In the context of short-term traffic congestion forecasting, it was evidenced that shallow machine learning (SML) models yielded superior results compared to DML models, as SML demonstrated efficiency in processing linearity, which contributes significantly to short-term traffic flow. Notably, the discussed short-term forecasting studies employing SML exhibited promising outcomes. Simultaneously, DML models showcased notable accuracy, given their adeptness in effectively handling both linear and nonlinear features. Furthermore, for real-time congestion prediction, it is imperative to consider models that entail minimal computational time, as high computational requirements are not feasible in such cases.

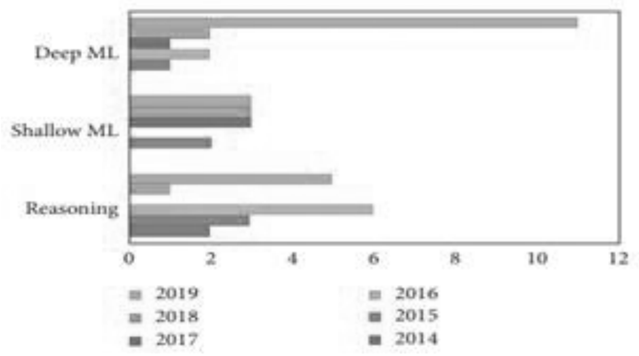

Figure 7: Application of AI models through years

Conclusions & Future Work

The utilization of a network comprising fuzzy components offers a range of advantages beyond those typically associated with distributed systems. Notably, the ease of configuration associated with fuzzy cells facilitates the incorporation of high-level functionalities, including the facilitation of mergers and decision-making processes. In the specific context of the presented application, namely, the utilization of agent-based modeling and fuzzy logic for simulating pedestrian crowds in panic decision-making scenarios, a network of sensors was deployed to intercept Bluetooth signals from mobile devices. Additionally, fuzzy logic was instrumental in determining the positions of pedestrians concerning escape routes and in calculating the optimal evacuation distances (Dumitrescu, 2021).

The primary aim of this research endeavor was to devise a comprehensive solution for the identification, tracking, and analysis of populations within panic-inducing situations. The potential applications of this solution extend across various domains, ranging from public transportation settings to Crisis Management systems. The future work lies in training more and more data and using probabilistic equations to improve the accuracy, implementing traffic congestion algorithm like Webster, Fuzzy method and Djikstra's algorithm in high complexity telecommunication networks. Proposing new modifications in increasing efficiency, optimization of throughput in high volume traffic congestion smart systems will be a tough task into the near future.

One might suggest that using Virtual environment for complex integrated systems can boost the outcomes in telecommunication networks. (Chu, 2006)Future work lies in using multiple of CNN to affect the training of a larger amount of data. For sure, it will demand greater computational cost, higher GPU processor performance to withstand the operation. Requirements of higher graphical processing unit card are prerequisites in adapting and preventing the drawbacks coming from large amount of computational cost and larger sets of data to be analysed. New GUI (graphical unit interface) also will be designed to replace ImageJ tasks and a software interface which is used to connect with common medical image programs like Slicer or Visualization Toolkit (VTK) will be designed. (Chu, 2006)

Reference List

Akhtar, M. &. (2021). A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation*, 1-18.

Alkandari, A. A.-S. (2014). Optimization of traffic control methods comparing with dynamic webster with dynamic cycle time (dwdc) using simulation software. *10th International Conference on Natural Computation*.

Carbonneau, R., Vahidov, R., & Laframboise, K. (2009). Forecasting supply chain demand using machine learning algorithms. In *Distributed Artificial Intelligence, Agent Technology, and Collaborative Applications* (pp. 328-365). IGI Global.

Chabchoub, A., Hamouda, A., Al-Ahmadi, S., & Cherif, A. (2021). Intelligent traffic light controller using fuzzy logic and image processing. *International Journal of Advanced Computer Science and Applications*, 12(4).

Chen, C. (2002). Freeway performance measurement system (PeMS). University of California.

Chu, P. P. (2006). *RTL hardware design using VHDL: coding for efficiency, portability, and scalability*. John Wiley & Sons.

Dumitrescu, C. C. (2021). Fuzzy logic for intelligent control system using soft computing applications. *Sensors*, 21(8), 2617.

Khazukov, K., Shepelev, V., Karpeta, T., Shabiev, S., Slobodin, I., Charbadze, I., & Alferova, I. (2020). Real-time monitoring of traffic parameters. *Journal of Big data*, 7, 1-20.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25.

Mascia, M., Hu, S., Han, K., North, R., Van Poppel, M., Theunis, J., ... & Litzenberger, M. (2017). Impact of traffic management on black carbon emissions: a microsimulation study. *Networks and Spatial Economics*, 17, 269-291.

Nishani E., C. B. (2017, June). Computer vision approaches based on deep learning and neural networks: Deep neural networks for video analysis of human pose estimation. *6th Mediterranean Conference on Embedded Computing* (MECO).

Sumayya, P. A., & Shefeena, P. S. (2015). Vanet based vehicle tracking module for safe and efficient road transportation system. *Procedia Computer Science*, 46, 1173-1180.

Patnaik, S., Yang, X. S., & Sethi, I. K. (2019). Advances in Machine Learning and Computational Intelligence Proceedings of ICMLCI 2019. *Proceedings of ICMLCI*, 1.

Liu, C., Sun, Y., & Christopher, L. (2015). 3D EM/MPM image segmentation using an FPGA embedded design implementation. *Journal of Signal Processing Systems*, 81, 411-424.

Yang, J., Zheng, H., & Louri, A. (2023). Versa-DNN: A Versatile Architecture Enabling High-Performance and Energy-Efficient Multi-DNN Acceleration. *IEEE Transactions on Parallel and Distributed Systems.*

Yuan, Y. &. (2023). Shot Boundary Detection Using Color Clustering and Attention Mechanism. *ACM Transactions on Multimedia Computing, Communications and Applications*.

Zhang, H., Yuan, H., Chen, Y., Yu, W., Wang, C., Wang, J., & Gao, Y. (2021). Traffic light optimization based on modified Webster function. *Journal of Advanced Transportatio*n, 2021, 1-10.