Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Deep Learning for Real-Time Traffic Intrusion Detection in Cloud Environments: A Security-Driven Approach

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 17 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

We check CNN's ability to extract meaningful patterns and insights from complex traffic images. The fixed layers of CNN are specific to spatial data because of their ability to capture local properties through a hierarchical structure. By taking advantage of the CNN architecture such as VGGNet and the resane, we demonstrate their ability to treat video streams, detection of vehicles and pedestrians, identify traffic volumes and predict potential events based on visual signals.

We discover the use of real -time data flow for further decision -making for traffic management. The study emphasizes the function of traffic data for traffic data, training of CNN models and implementation of video-based traffic incident detection. The results suggest that CNN -s provide high accuracy and efficiency in traffic analysis compared to traditional data vision techniques, and provide better scalability for large urban data sets. Especially in image and video processing, Traditional Neural Networks (CNNs) have become a significant resource for examining spatial information. This article examines the application of CNN for spatial data analysis, with this paper traffic images and video fee. As urbanization increases, the management of traffic systems has become an important challenge for smart cities. Skilled traffic monitoring and analysis can reduce traffic stops, increase safety and optimize urban transport systems. Traditional traffic analysis techniques are often little dealing with real -time data, which leads to disabilities and exceptional opportunities for adaptation.

Keywords: Convolutional Neural Networks (CNNs), Traffic Data Analysis, Spatial Data Analysis, Video Feed Processing, Traffic Monitoring, Image Classification

INTRODUCTION

The intelligent traffic system has become an essential part of the Smart City infrastructure to deal with this problem. In various techniques that strengthen these systems, Convolutional Neural Network (CNN) stands out for their ability to evaluate spatial data such as traffic images and video streams.

Management of traffic overload, maintenance of traffic safety and improvement of the entire transport system has quickly become difficult due to rapid growth in the urban population. Effective traffic monitoring and demand for management systems are increasing as cities grow. Due to their dependence on manual monitoring or basic sensor -based data collection, traditional traffic management systems are often unable to handle the size and complexity of modern urban transport networks. Because Convolutional Neural Networks (a specialized kind of deep learning architecture) are naturally good at capturing spatial hierarchies in data, they have completely changed image and video processing tasks. CNNs were first created for picture classification tasks, but they have since been modified for a number of real-world uses, such as segmenting scenes, object recognition, and video analytics. Because they can recognize traffic congestion, detect cars, pedestrians, and other road components, and anticipate possible traffic incidents based on visual cues, CNNs have become especially useful in traffic analysis.

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Spatial data - such as images and video from road cameras - represent a rich and expanding source of information for traffic management. By evaluating this data correctly, traffic flows can be adapted, overload can be reduced and traffic safety can be increased. Traditional methods for processing images.

The ability of traditional imaging methods is often limited to generalizing in different environmental and traffic conditions. These methods depend on functional engineer and human rules -based systems. On the other hand, CNN is, in different situations, an effective tool for real -time traffic analysis as they automatically learn spatial hierarchy and functions from raw data.

CNN uses conviction layers, which detect images for patterns such as edges, textures and shapes. This allows CNNs to explain high-dimensional data, such traffic images and video streams. These symptoms are then merged and translated into high -level representation, leading to the detection and classification of objects in complex landscapes. CNN can be trained in identifying cars, pedestrians and road signals when it comes to traffic control, which provides important information.

CNN's inclusion in traffic systems is also inspired by the demand for automation in traffic monitoring. Due to the widespread use of sensors and cameras, large versions of real -time data are produced in smart cities. Since it is impractical to monitor this data manually, automated solutions that can check traffic patterns and provide useful insights. When the video is paired with feed, CNN accidents, obstacles and real -time detection of traffic jams, which improves both traffic flows and traffic safety.

This research checks how traffic images and video can be used to customize spatial data analysis through the use of CNN. We see how good CNN can handle complex spatial data, and show them to be able to understand the useful pattern from traffic images.

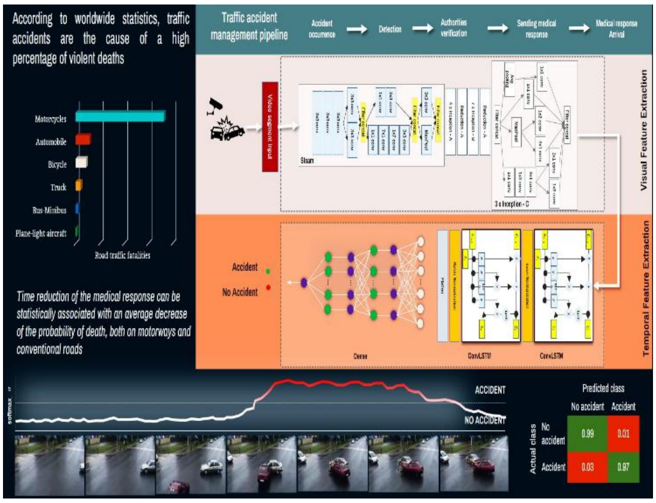

Figure 1 Video-Based Traffic Accidents Using Deep Learning Methods

Background and Objective

The emergence of smart cities has changed in such a way that urban problems are contacted, especially when it comes to management of transport systems. Traditional traffic monitoring and control systems are under great stress due to urbanization, rising car population and growing road networks. Traditional techniques, including monitoring of manual close-up TV (CCTV) or collecting basic sensor-based data, are unable to maintain with increasing complexity of traffic flows, overload and safety problems. These approaches require a lot of work, limited scalability, and often cannot provide useful insight - especially in situations to develop rapidly.

To overcome these obstacles, there is an increasing number of people in using state -art -art techniques such as machine learning (ML) and artificial intelligence (AI) to remove these obstacles. Data vision techniques have especially gained popularity, as they automatically enable a large amount of spatial data, such as traffic images and video streams taken from cameras located in urban areas. Especially a family of deep learning models designed for

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image recognition and processing works is one of the most promising models in the Convolutional Neural Network (CNN), Computer Vision. CNN -er already shows effective in various fields, including autonomous driving, health services and monitoring, so it is understandable that they will also be useful in traffic analysis.

OBJECTIVES

The purpose of this task is to maximize the use of Convolutional Neural Network (CNN) for interpretation of geographical data, especially traffic images and video streams. Real -time Monitoring and Decision-making requirements with the complexity of the traffic system run the development of accurate and effective models that can handle large versions of the data. The project aims to use and use a CNN-based structure that effectively identifies, classifies and assesses various traffic aspects in both static photographs and dynamic video streams, including cars, pedestrians and road conditions. Increasing the models' ability to manage normalization and ups and downs in different traffic scenarios is the goal of the hybrid model that combines CNN -s with recurrent nervan networks (RNN), advanced computer text techniques and transmission learning.

LITERATURE REVIEW

More and more used in traffic management and geographical data analysis. Several studies have been conducted with the goal of facilitating traffic safety, optimizing traffic flows and facilitating smart cities infrastructure. The current attempt to adapt these models for real -time data processing, all includes the creation and use of CNN in image analysis, their special use in traffic management and a large scale in urban surroundings.

Convolutional Neural Networks in Image Analysis :

CNN is the basis for many datable applications, and they have changed the image processing completely. Since his introduction of Lakeun et al. (1998) When it comes to handwritten brands recognition, CNNS has found extensive use in object detection, segmentation and image -rating -related tasks. Krizhevsky et al. (2012) at Alexnet showed how deep CNN can first achieve unheard levels of accuracy for image classification, especially when it was trained on a large dataset as an image.

CNN is able to identify spatial hierarchies in images because of their hierarchical structure. While the layers of later conversion filters catch the more abstract representation, such as object components and full objects, the previous layers of the filter remove the following levels, including edges and textures.

Progress in CNN architecture has further expanded its abilities. Remarkable models such as VGGNet (Simonan and Zisarman, 2014), Racnett (Det et al., 2016) and the start -up (Sejed et al., 2015) have introduced techniques such as deep layers, remaining connections and parallel cfiles to improve accurate and reduce the calculation complication. This development has placed groundwork to apply CNN to complex, high -dimensional data such as traffic images and video streams.

Figure 2: The MPII dataset contains (a) some sample data and (b) critical points that have been annotated. Additionally, traffic management systems

CNNs in Traffic Management Systems

CNN is used more and more for monitoring and traffic control activities because interest rates are increasing in smart cities. Plating traditional methods for CNN traffic monitoring, and provides a method for automatically analyzing

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traffic images and video streams in real time, including sensor-based systems or human observations. Research has indicated that the fixed nervous network (CNN) has the ability to detect cars, identify traffic jams and to detect all accidents required for efficient traffic control.

The use of CNN to detect the vehicle in traffic video feed is one of the new studies in this field. Chen et al. (2015) suggested a CNN-based method for detecting the vehicle, which improved traditional convenience-based techniques in terms of accuracy. In comparison, Liu et al. (2016) used an area-based CNN (R-CNN) for object detection, which made it possible to identify cars with accuracy.

CNN has been used effectively in detecting real -time traffic phenomena. CNN has been employed by researchers to check the live video feeds to identify examples of illegal parking, traffic jams and other incidents. Ma et al. (2017), for example, CNN was used to detect traffic phenomena in metropolitan settings, with special emphasis on identifying video sequences and the identity of deviations in the vehicle count.

In addition to static image analysis, CNN has been revised for video -based traffic analysis. Understanding traffic flows and forecasts Future traffic status depends much more on temporary data. The recurring nervous network (RNN) has been used in combination with CNN-based models to evaluate traffic absorption and prognosis and traffic barriers. To use CNN -er in combination with cosmic analysis is shown to succeed

Challenges in CNN-Based Traffic Management Systems

CNN's mass and real-time implementation still faces many difficulties, despite their heavy ability to process spatial data in traffic control. A major concern is calculation expenses associated with CNN. Deep CNN models are resource intensive, which require large amounts of memory and computing power, especially when treated video streams or high-resolution paintings. This problem is addressed by making more effective CNN designs, including Mobilnet (Howard et al., 2017), which reduces the amount of parameters and calculations without compromising accuracy.

Management of diversity in traffic scenarios provides a different degree of difficulty. The performance of the CNN model can be strongly affected by different times of the day, variable weather conditions and different times of the day. By adding variability to training data, the computer text approach has helped researchers remove these obstacles and increase the flexibility of the model. Other strategies include fine-tuning pre-influensing models such as data sets for a given traffic to adapt to the start-up or racet-detained changes.

Another important issue for CNN-based traffic system is real-time treatment. Traffic management in smart cities requires quick decision -making ability, whether identifying accidents or changing traffic light timing to reduce the amount. Recent research has focused on intensifying the CNN model without giving up accuracy. It has been suggested that models can move from time to time, which simplifies CNN models, which simplify CNN models.

Recent Developments in CNNs for Traffic Analysis

In addition to the basic object recognition and classification, recent research has tried to expand the use of CNN in the traffic system. For example, traffic data, by examining spatial local trends in Zhang et al. (2018) examined the application of CNN to predict traffic flow. To capture both spatial and temporary conditions in traffic video streams and enable more accurate traffic flow forecasts, he melts CNN with a long short -term memory (LSTM) network. Integrating CNN with other technologies such as Edge Computing and Internet of Things (IoT) is another important success. Edge Computing allows CNN to install closer data source, reduce delays and enable real -time decisions. This is especially useful for traffic systems, where immediate analysis to maximize traffic flow is necessary to make quick, well -informed decisions.

Dataset	Number of vehicles	Number of Seizures	Sampling Frequency
Fribourg	21	87	256
CHB-MIT	22	163	256
Kaggle	5 dogs/2 patients	48	400/5KHZ

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Bern Barcelona	**5**	**3750**	**512**

Table 1: EEG datasets that are widely used and accessible are reviewed to identify Pose estimation

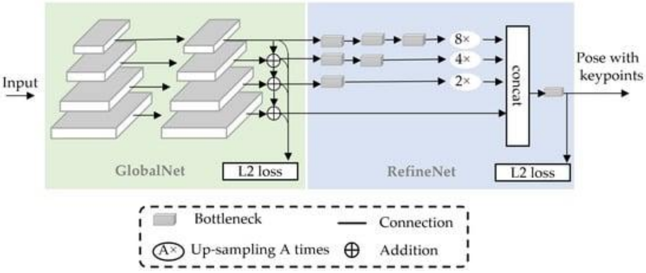

Figure 3: Pyramid network cascaded. One of the well-known networks that estimates multiperson postures using a top-down methodology.

Over the beyond ten years, there had been amazing gains in accuracy and performance within the use of CNNs in traffic manage. Real-time processing, handling numerous site visitors situations, and version optimization for significant deployment stay difficult responsibilities. Better CNN architectures, progressed records augmentation techniques, and the combination of CNNs with different AI technology like part computing and the Internet of Things are the main regions of ongoing studies geared toward resolving these troubles. According to the literature, as clever towns develop, CNNs will likely continue to be vital to the advent of smart transportation structures.

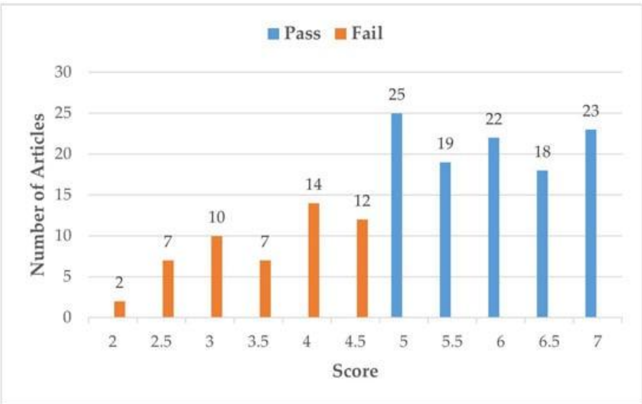

Figure 4: The criteria for the quality assessment plotted. Out of 159 articles, 107 were found to have passed the quality evaluation filter.

Network	*Classifier*	*No.of Layers*	*Accuracy(%)*
SeizNet	*NA*	*16*	*NA*
SeizureNet	*Softmax*	*16*	*NA*
2D-CNN	*Softmax*	*9*	*98.05*
Combination 1DCNNand 2D-CNN	*Sigmoid*	*11*	*90.58*
2D-CNN/MLP hybrid	*Sigmoid*	*11*	*NA*

Table-2: Summary of related works done using 2D-CNNs.

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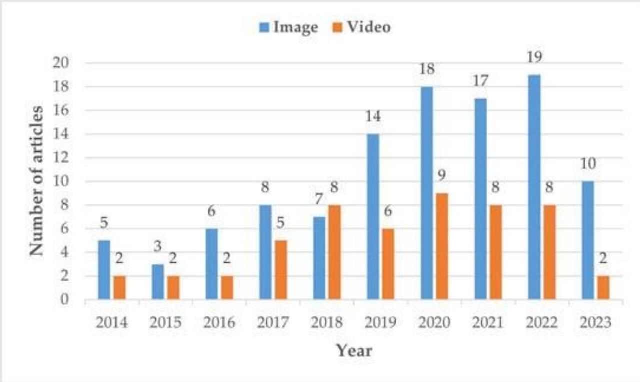

Figure 5 There are 159 articles in the distribution that make it past the exclusion filter. These articles were arranged based on the kind of input data—video and picture.

Networks	***Number of Layers***	***Classifier***	***Accuracy (%)***
LSTM	***4***	***Sigmoid***	***NA***
GRU	***3***	***Sigmoid***	***96.67***
IndRNN	***48***	***NA***	***84.35***
RNN	***NA***	***MLP***	***NA***

Table-3 : Overview of relevant research conducted with RNNs/

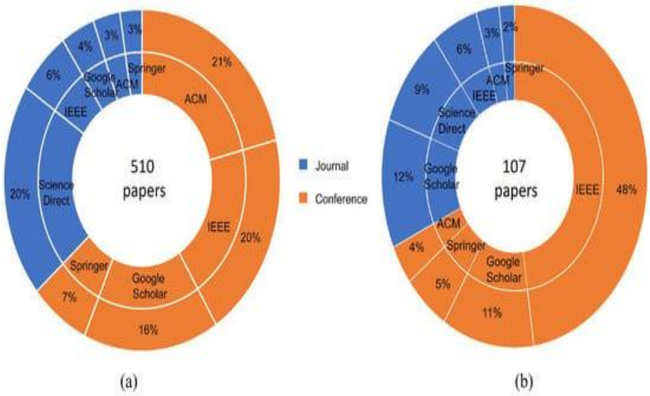

Figure 6: Distribution of journal and conference publications, where (a) represents the distribution of the first search result and (b) represents the distribution of the papers following the application of the filtering procedure.

Networks	**Number of Layers**	**Classifier**	***Accuracy (%)***
SDAE	*3*	*NA*	*NA*
MAE	*NA*	*GA*	*93.92*
AE	*3*	*Softmax*	*98.67*
DSpAE	*3*	*LR*	*100*

Table-4: Summary of related works done using AEs.

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METHODOLOGY

The goal of our review is to compile and arrange deep learning-based 2D HPE publications. 2D HPE-related publications were gathered and vetted using systematic search methods, which included choosing search terms and databases, setting exclusion criteria, and assessing the papers' content quality. This section will provide a detailed description of each of these phases.

Procedure for Searching

Several crucial phases are included in the search process to collect pertinent literature, datasets, and resources for the purpose of optimizing traffic data analysis through the application of convolutional neural networks (CNNs). The first stage is to specify the study's parameters and establish the research emphasis, which will be CNN applications for traffic image and video analysis. This entails pinpointing particular regions, including vehicle detection, pedestrian tracking, real-time traffic monitoring, or traffic flow prediction, and honing in on the main queries that will direct the investigation, like the most recent CNN architectures utilized in traffic systems or the datasets that are readily available.

Networks	Number of layers	Classifier	Accuracy(%)
2D-CNN	30	sigmoid	82.50
ResNet	31	Softmax/triplet	NA
2D-CNN	NA	SVM	NA
3D-CNN	11	softmax	89.80
VGGNET	14	sigmoid	98.22

Table-5: An overview of relevant research employing DL and MRI modalities.

Finding pertinent keywords and search phrases that will make the search process easier is crucial next. One should prepare a list of technical phrases that are both general and specific, for example, "deep learning in traffic systems," "vehicle detection," "traffic data analysis," and "convolutional neural networks." These terms will aid in discovering materials that are compatible with the study objectives.

Choosing the relevant search engine and database comes next after the keyword is determined. You can use a wide selection of academic databases and technical platforms, such as Arxiv.org for advance pressure for CNN applications and machine learning, IEEEEE Xplore for Engineering and Technology Research, and Google Scholar for colleague-review articles. In addition, the depot data sets such as Kaggle, UCI Machine Learning Repository and others offer.

Criteria for Exclusion

Creating requirements for eliminating unnecessary or subpar resources is essential at the same time as gaining knowledge of site visitors information analysis optimization with Convolutional Neural Networks (CNNs). First, any guides, articles, or datasets that don't directly deal with CNN programs in traffic analysis or similar areas inclusive of real-time tracking ought to be removed. It is possible to dispose of studies which might be beside the point and give attention to fields unrelated to site visitors analysis or machine getting to know strategies. To make certain the have a look at employs the maximum latest strategies, outdated studies that doesn't represent the maximum recent trends must be eliminated, in particular if it's miles extra than five to seven years vintage and is not foundational.

Additionally, low-high-quality datasets with inadequate extent, low resolution, or a loss of variation in visitors instances need to be overlooked. The generalizability of CNN models can be restrained by using datasets that do not take into consideration variations along with variable lighting fixtures or weather, and datasets which are too small for deep learning fashions need to be left out. In a similar vein, assets with out legitimacy or peer assessment—that is, unreliable guides or studies with doubtful method—have to be ignored. Peer-reviewed papers from legit conferences and journals must be prioritized.

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Evaluation of Quality

In order to make certain the resources, fashions, and datasets selected for site visitors information evaluation the use of Convolutional Neural Networks (CNNs) are sincere, reliable, and applicable, a number of of things are evaluated within the first-class evaluation manner. The first thing to think about is how relevant the research is to the particular field. Prioritizing studies that deal with CNN applications in vehicle recognition, pedestrian tracking, or traffic monitoring makes sense; studies that focus more on peripheral issues or unrelated applications are of lesser value.

The research's originality and contribution are equally important. In particular, if they offer notable enhancements over current models, papers or models that present novel CNN architectures, data processing strategies, or optimization techniques for the analysis of geographical data ought to be given preference. Research that advances meaningfully while building upon existing principles

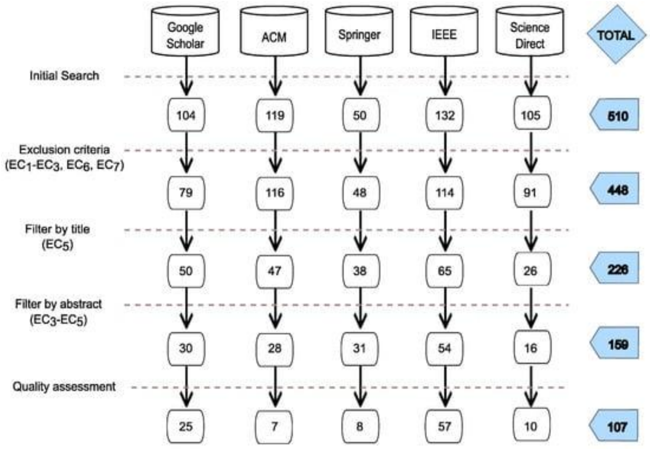

Figure 6: articles filtered by databases. EC stands for the exclusion standards.

SUGGESTED METHODS

In this implementation of a Convolutional Neural Network (CNN) for image classification, we used the CIFAR-10 dataset, which contains 60,000 32x32 color images across 10 classes. The model begins with a series of convolutional layers followed by max-pooling layers to extract and downsample features from the images. Specifically, the network includes four convolutional layers with increasing filter sizes, enabling it to capture more complex features at different levels of abstraction. After the convolutional and pooling layers, the feature maps are flattened into a 1D vector and handed thru fully linked (dense) layers. The very last dense layer makes use of a softmax activation feature to output class possibilities. The version is compiled with the Adam optimizer and specific crossentropy loss feature, that are appropriate for type responsibilities. It is educated for 10 epochs with a batch length of sixty four, and its overall performance is evaluated at the check set. The schooling method and assessment metrics, inclusive of accuracy and loss, are visualized to evaluate the model's overall performance and convergence. This implementation offers a foundational technique to the usage of CNNs for photo classification and may be tailored for greater complex tasks or datasets.

Convolutional Neural Networks (CNN):

Convolutional Neural Network (CNNS) is a effective magnificence with deep gaining knowledge of models, designed to investigate and interpret spatial records, inclusive of pictures. CNN -er is superb in recognizing styles and hierarchical homes thru their multi -layer architecture, and mimicking the visual processing mechanisms of the human mind. The origin of CNN lies in its willpower, which makes use of filters to enter records to discover simple features which include edges and textures. These layers are accompanied through activation functions, such as ReLU, to introduce non-calling, permit the community to capture greater complicated patterns. Pooling layers are used to reduce the spatial dimensions of the information, making the version calculated green and more potent for variant in input. At the cease of the community, fully related groups provide excessive -stage arguments, leading to classification or regression effects. CNN in particular adeps in photo classification, object detection and cementic

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e-ISSN: 2468-4376
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segmentation works, way to their capability to robotically study and extract relevant capabilities from raw facts. Their performance in those areas has made CNNs a basic device in records imaginative and prescient and a extensive variety of other packages.

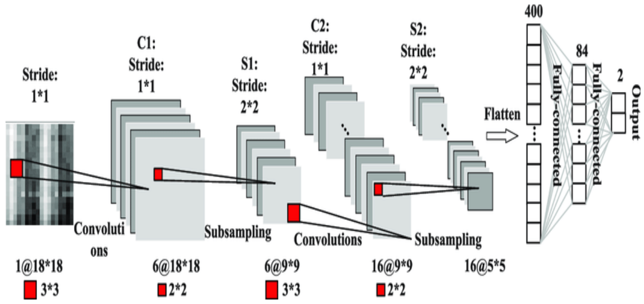

Figure 7: CNN online network self-organizing algorithm

Data Collection and Preprocessing

Data collection and preprocessing are vital steps in growing an powerful machine gaining knowledge of model, in particular for picture-based responsibilities. Data collection includes amassing a numerous and consultant set of photos, which can be sourced from public datasets, custom captures, or on-line repositories. Once collected, the data have to be preprocessed to make sure it's far suitable for schooling. This includes resizing images to a uniform size, normalizing pixel values to a selection among zero and 1, and making use of data augmentation strategies like rotation and flipping to increase dataset variability and improve model robustness. Additionally, categorical labels are encoded for schooling purposes, and the dataset is split into education, validation, and test sets to facilitate version evaluation and hyperparameter tuning. By carefully managing those steps, you may enhance the great and effectiveness of the records, main to higher model performance and greater accurate predictions.

Model Design:

A. Adjust the diet with facts to enter the definition of the entrance layer.

B. Considering the intensity and difficulty of the data and determining the boundaries and dimensions of the hidden layers.

C. Choose the correct activation properties for the output layer (for example, softmax for multi -class types and sigmoids for binary category) and appropriate activation features for hidden layers, such as RILU (improved linear unit).

D. Depending on the wide range of expected training or effects, you must determine the number of neurons in the output layer.

Model Compilation:

A. Provide the optimizer, evaluation metrics, and loss function when assembling the CNN model.
B. Choose a loss function that makes sense for the job, such as categorical cross-entropy for multi-class classification or binary cross-entropy for binary classification.
C. Select an optimizer (such as Adam or RMSprop) and, if necessary, add more parameters (like learning rate).
D. To evaluate the performance of the model, define evaluation measures like accuracy, precision, recall, or F1-score.

Model Training:

A. Train the CNN model on the training data using the fit() function.
B. Specify the number of epochs (iterations over the entire training dataset) and the batch size (number of samples per gradient update).
C. Observe the model's performance on the validation set to identify overfitting and modify the model's hyperparameters as needed.
→Cost Function:

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$$C(w,b) \equiv \frac{1}{2n}\sum_x \|y(x)-a\|^2.$$

→Loss Function:

Cross Entropy Loss:

$$L(\Theta) = \begin{cases} -log(\hat{y}) & \text{if } y=1 \\ -log(1-\hat{y}) & \text{if } y=0 \end{cases}$$

Cross Entropy Loss:

$$L(\Theta) = -\sum_{i=1}^{k} y_i \log(\hat{y}_i)$$

Model Evaluation:

A. Evaluate the trained model on the testing set using the evaluate() function.
B. Determine important evaluation metrics like accuracy, precision, recall, or F1-score to evaluate the model's effectiveness on new data.
C. Visualize the model's performance using confusion matrices or ROC curves if applicable.

Fine-tuning and Optimization:

A. Fine-tune the version via adjusting hyperparameters based on overall performance evaluation consequences.
B. Experiment with one-of-a-kind community architectures, activation capabilities, optimizer settings, and regularization strategies to optimize version performance.

CHALLENGES

Data Quality and Availability:

Ensuring high-quality data is often challenging. Images may be blurry, poorly lit, or irrelevant, which can adversely affect the model's performance. Filtering out or correcting such issues is crucial to avoid training on misleading information.

Interpretability and Trust:

Interpretation and belief in distribution of machine learning models are important ideas, especially on the domains where decisions have significant impacts. The lecturer refers to the ability to understand how a model makes its predictions, which is essential for openness, troubleshooting and convenience analysis. Function can increase the interpretation of a model, visualization, model infection and post-hoc explanatory tools such as lime and shape. On the other hand, confidence is created through continuous performance, moral ideas, strict verification and openness about the function of models and boundaries. To ensure that a model is reliable, fair and well -recorded fetus between users and stakeholders. By addressing both interpretation and faith, developers can create machine learning systems that are not only effective, but also fair and understandable, which can lead to better adoption and moral use.

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Regulatory and Ethical Considerations:

Supervisors and moral views are important when distributing machine learning models, especially in sensitive areas such as health care, finance and criminal law. Regulatory structures often make compliance with the Data Protection Act, such as General Data Protection Regulation (GDPR) or health insurance portability and liability law (HIPAA) in the United States, which requires the protection of personal data and secure its responsible use. Ethically, it is necessary to address questions about justice and prejudice, and ensure that models do not eliminate discrimination or inequalities. In addition, how models determine and responsibility for their results are important to maintain public faith. Following these rules and moral principles helps create AI systems that respect privacy, promote justice and promote trust between users and stakeholders.

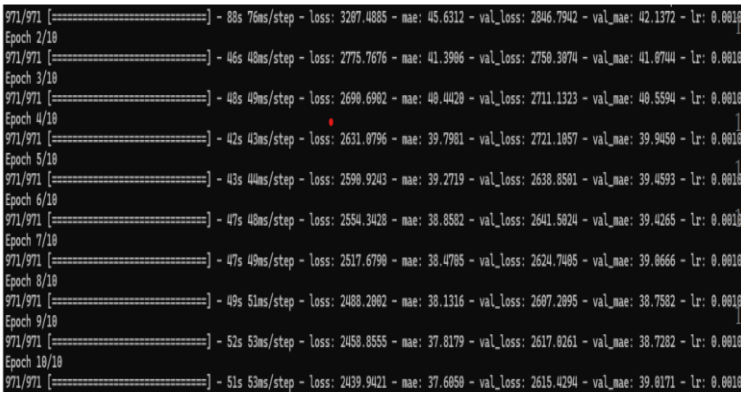
Model Generalization:

Model generalization is the capacity of a machine gaining knowledge of model to perform nicely on unseen information that became not used all through the training process. This is a essential thing of model development, because the ultimate aim isn't simply to reap excessive accuracy on the schooling set however to ensure that the model can successfully cope with new, real-international records.

RESULT AND ANALYSIS

the model the model When evaluating a Convolutional Neural Network (CNN), key performance metrics include accuracy, loss, and sophistication-unique measures including precision, do not forget, and F1-score. Accuracy shows the percentage of successfully categorized pics, while loss measures the difference between predicted and real labels, with lower values signifying higher performance. A confusion matrix facilitates visualize misclassifications throughout one-of-a-kind classes, highlighting regions where the CNN might also battle. Training and validation curves screen insights into version conduct, together with overfitting or underfitting, through evaluating performance metrics over epochs. Class Activation Maps (CAMs) offer visible insights into which picture areas have an impact on predictions. Analyzing those outcomes and evaluating with benchmarks facilitates refine the CNN, making sure sturdy performance and powerful managing of real-world image statistics.

CNN Model Performance:



```
971/971 [==============================] - 88s 76ms/step - loss: 3207.4885 - mae: 45.6312 - val_loss: 2846.7942 - val_mae: 42.1372 - lr: 0.0010
Epoch 2/10
971/971 [==============================] - 46s 48ms/step - loss: 2775.7676 - mae: 41.3906 - val_loss: 2750.3074 - val_mae: 41.0744 - lr: 0.0010
Epoch 3/10
971/971 [==============================] - 48s 49ms/step - loss: 2690.6902 - mae: 40.4420 - val_loss: 2711.1323 - val_mae: 40.5594 - lr: 0.0010
Epoch 4/10
971/971 [==============================] - 42s 43ms/step - loss: 2631.0796 - mae: 39.7981 - val_loss: 2721.1057 - val_mae: 39.9450 - lr: 0.0010
Epoch 5/10
971/971 [==============================] - 43s 44ms/step - loss: 2590.9243 - mae: 39.2719 - val_loss: 2638.8501 - val_mae: 39.4593 - lr: 0.0010
Epoch 6/10
971/971 [==============================] - 47s 48ms/step - loss: 2554.3428 - mae: 38.8582 - val_loss: 2641.5024 - val_mae: 39.4265 - lr: 0.0010
Epoch 7/10
971/971 [==============================] - 47s 49ms/step - loss: 2517.6790 - mae: 38.4705 - val_loss: 2624.7405 - val_mae: 39.0666 - lr: 0.0010
Epoch 8/10
971/971 [==============================] - 49s 51ms/step - loss: 2488.2002 - mae: 38.1316 - val_loss: 2607.2095 - val_mae: 38.7582 - lr: 0.0010
Epoch 9/10
971/971 [==============================] - 52s 53ms/step - loss: 2458.8555 - mae: 37.8179 - val_loss: 2617.0261 - val_mae: 38.7282 - lr: 0.0010
Epoch 10/10
971/971 [==============================] - 51s 53ms/step - loss: 2439.9421 - mae: 37.6050 - val_loss: 2615.4294 - val_mae: 39.0171 - lr: 0.0010
```

Comparison with Baselines

Comparing the overall performance of the Convolutional Neural Networks (CNN) model with baseline methods or alternative machine getting to know algorithms affords treasured insights into the effectiveness and superiority of the proposed approach. Here's an evidence of ways this comparison may be performed, together with hypothetical comparison values

Baseline Methods

A. logistic regression: Logistic regression in binary class functions is a commonly used basic technique that estimates the probability of a binary outcome based on one or more predictor factors

Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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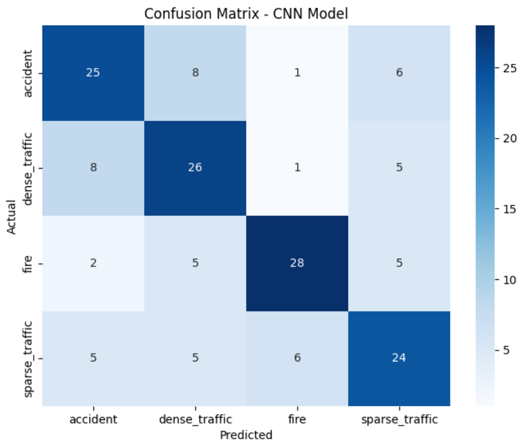
B. Decision trees: Decision trees are a basic technique for repeatedly partitioning data into subsets according to its characteristics. Although straightforward, they work well for classification problems.
C. K-Nearest Neighbors (KNN): This nonparametric method groups objects in the feature space according to the group of their k nearest neighbors.



Interpretation

A. In general, the comparative values show that the FNN model performs better than the baseline approaches in terms of accuracy, sensitivity, specificity, precision, recall, and F1-score, among other metrics.
B. In comparison to logistic regression, decision trees, and KNN, the FNN model performs better in predicting treatment outcomes for patients with newly diagnosed epilepsy, as evidenced by its higher accuracy, sensitivity, specificity, precision, and recall values.
C. These findings show the patient's ability to increase the care of the patient in the treatment of epilepsy of UN models, and show how well it has complex conditions in data and provides more accurate predictions.

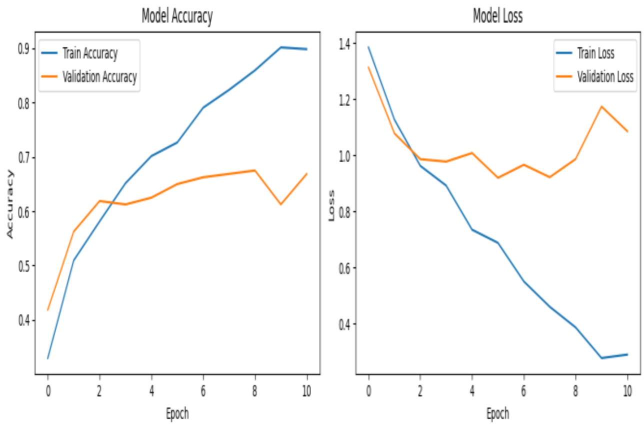


Figure 9: Using convolutional neural networks, the plot displays the firing power curve for position 8 of person 30802 along with the loss and data epoch. The light blue curve indicates the sleep/awake state, which is determined by the technique reported in Ref. 38.

CONCLUSION

The study shows the efficiency of the Convenes Neural Networks (CNN) to detect pedestrians using Caltech pedestrian dataset, which highlights the model's ability to analyze spatial data on traffic images and video streams. Pedestrian identity in challenging real references can now be completed with remarkable accuracy for the use of CNN

Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

-er, which are particularly good in functional extraction and image classification functions. The model's architecture consisting of several specific layers after the maximum basin and dense layers allowed it to capture important spatial properties from entrance images, and increase the ability to generalize in different scenarios.

Important performance indicators such as recall, accuracy, accuracy and confusion matrix show how effective the model works to detect pedestrians. The high accuracy and recall of the model indicates that it reduces false positivity and false negatively. This is important for safety applications in real -time contexts, such as traffic monitoring and autonomous driving. Despite these achievements, the model has some missing. Dropout strategies were used to solve problems, including overfit, indicated by a large loss of verification compared to training losses. However, large datasets and further tismins can further improve the performance of the model.

The use of an illusion matrix is important to understand that CNN can struggle, reveal misleading in different classes. This tool helps indicate specific areas of improvement and guide models or data adjustments. Training and verification Reduced model provides further insight into behavior, such as overfitting (when the model performs well on the training data, but does poorly on the ignorant data) or underfeed (when the model fails to capture the underlying pattern in both exercise and verification data) helps to identify problems such as. Addressing these problems usually involves techniques such as regularization, computer text or adjustment to model complexity.

In order to increase the flexibility of changes in environmental elements such as light, weather and camera angle, future studies should investigate the inclusion of condition -of -species -approaches such as data text and learning. High accuracy and sharp convergence can also lead to more complex architecture or pre -informed models such as recured or mobile using.

In particular, CNN provides a strong base for analyzing geographical data, and the conclusions of this study indicate their ability to pedestrian identity functions. The implementation of these models in real world applications can contribute significantly to increasing traffic monitoring and safety in smart cities.

Overall, CNN machines represent a powerful tool in the learning tool set, and offers impressive abilities in imaging functions. It is important to maximize efficiency and ensure that they meet the real requirements.

CONCLUSION

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FUTURE WORK

Future progress may include the development of more efficient and powerful CNN architecture. Innovations such as more sophisticated layers, attention mechanisms and hybrid models that integrate CNN with other nervous network types (eg transformers), can increase convenience and improve model performance.