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Road Traffic Condition Monitoring using Deep Learning

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Abstract-

Massive amounts of information about vehicular traffic are added to the traffic monitoring system every second. Keeping an eye on these metrics demands a lot of time and labor. It is possible to use a deep learning method (Convolutional Neural Network) for traffic management and control. The training dataset is built using pre-processed traffic monitoring data.

Constructing the Traffic net entails retraining the network on data from traffic-related applications and shifting the network to the new domain. There are several large-scale uses for this Traffic net, one of which is regional detection. More importantly, it has widespread applicability. Faster finding and higher precision in the case study are impressive proof of efficiency. The preliminary evaluation may lead to its implementation in a traffic monitoring system and may eventually improve the intelligent transportation system.

I. INTRODUCTION

The Intelligent Transportation System (ITS) is a cutting-edge programmed with several potential uses in modernizing the transportation sector. Solutions that are tailored to various forms of Transportation and Traffic Control. The congestion on the Road during rush hour is a direct result of the rising popularity of personal transportation vehicles. In turn, this makes it much more time-consuming and difficult to keep tabs on traffic conditions over wide areas. There are too many camera outputs for a single person to watch all day long, and the Traffic Monitoring hall has thousands of monitors showing the real-time traffic flow. Large numbers of people are needed to keep tabs on traffic conditions and make congestion forecasts. We've used a Deep Learning Algorithm to foretell traffic congestion to save time and eliminate the possibility of human mistake. An important part of intelligent transportation systems is categorizing the congestion. When it comes to using ITS, public safety and emergency services are by far the most common. The following Fig.1 provides a high-level overview of the planned study.

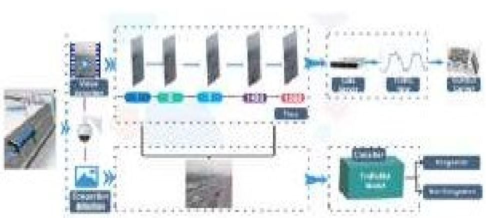

Fig. 1.Architectural overview

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The goal of this effort is to develop a fast traffic detection system that uses less manpower and can identify Multiclass Objects. Challenges such as monitoring for fires, accidents, and heavy and light traffic. The goal is to use the trained model from the input dataset to determine whether the input picture is dense or sparse.

II. LITERATURE SURVEY

One well-known kind of deep neural network is the convolutional network, which extracts features from input data and previously-learned features. Removed from the picture in a straight line. CNNs are more likely to accurately classify objects because they learn characteristics as photos are collected, rather than via pre-training [1]. The traffic flow is calculated under varying conditions using dynamic temporal prediction. The forecasting process is executed on two time scales, one with a short length of 7 days and the other with a long duration of 30 days. It has been done in real time and online with the help of deep learning [2]. DSRN is used for cellular classification in Hep-2 images [3]. Traffic Net's ability to distinguish between crowded and empty stretches of road has been enhanced [4]. To get to Image Net VID 2017, FGFA and Deep Feature flow are suggested [5]. The LSTM model is used to estimate the length of a section in a work of fiction [6]. Extensive tests are performed to evaluate the performance of a small set of typical Benchmark techniques, such as TC-128, OTB-100, and VOT2015 [7]. In [8], we propose and train a CNN-based Speckle Net with 3600 speckle patterns, and then activate its output layer to serve as a classifier for a support vector machine. Ship detection using synthetic aperture radar (SAR) photos is one area where CNNs have been put to use [9].
In order to handle video data in a systematic manner, the IT'S employs trained CNN. In order to evaluate the efficacy of the classifiers, the results are compared to those produced by classifiers based A combination of multilayer perceptions (MLPs) and a deep neural network (DLNs) equipped with auto encoders. The suggested technique is less dependent on the quality of the video data and more accurate [10].

III. EXISTING METHOD

It's a hassle to have to manually identify and categories each car. Here we provide two automatic id/classification algorithms. In order to recognize and categories automobiles based on acoustic signals captured by microphones placed along the roadways, two machine learning techniques are used, namely Artificial Neural Network (ANN) and Nearest Neighbor (KNN).Only a double-ended, winding route with a wide variety of vehicles adds difficulty to the manual prediction procedure. Applying the automated detection technique simplifies this situation (ANN & KNN). As a classifier, ANN & KNN roughly divides cars into three groups: those operating in high, medium, and low volumes of traffic. Cars may be detected using microphones to capture the acoustic signals being emitted by the vehicles. When a car drives over the microphone, the signal is recorded and shown as an energy peak. Smoothing out the energy contour allows for automated detection of the vehicle by identifying the energy peak. The feature vectors are used to train the ANN/KNN classifiers. The effectiveness of the technique is evaluated across a variety of areas using the Test data set, which includes more than 180 automobiles. In Fig.3 we see the schematic representation of the whole system.

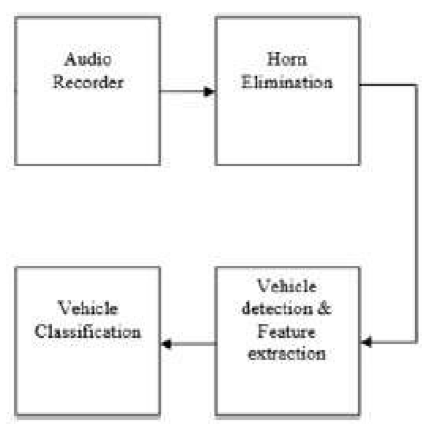

Figure 3.Modeling the Whole System

We may divide the current setup into three distinct eras:

Obtaining Information

Vehicle detection-based classification follows data preprocessing.

First, we must gather information.

The microphones are first stationed along the roadway, some distance from the bus stop, to aid in the data collecting process. It records information on the noise made by passing automobiles. The second

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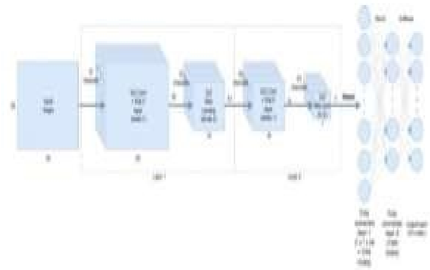
is the employment of a Sony handy camera with a Zoom H4N Handy Noise Recorder for capturing noise-free video in real time. A classification scheme is developed based on the data obtained and includes the following four classes: Type, Peak, Vehicle, and Peak Point Groupings.
Second, data preparation
The algorithm operates via the following steps:
1. The signaling time is based on a Hamming window of 20 milliseconds.
Second, we use FFT to get the spectrum for each window, which we then use to depict as an absolute value.
Third, have a look at the frequency component and spectral peak.
Fourth, the 3-5 kHz frame is discarded if the Peak value is discovered to exist there.
Fifth, this algorithm analyses the complete signal to identify vehicles and categories them.
Third, we use vehicle detection to categories.
The peak selecting technique is used to determine the total number of vehicles. For anyone interested in the peak-finding algorithm, it goes as follows. Each 10 ms window's worth of the Energy contour is analyzed to get its highest dB values. The possible peak values are determined by comparing the values of nearby samples. Vehicle count is calculated from processed signals. Mel Frequency Campestral coefficient character vector is used for data training. Roughly 80 examples of each vehicle type are used as test data. Classification accuracy is evaluated by contrasting the outcomes.

IV. PROPOSED METHOD

To determine the traffic state (dense or sparse) from the input picture, a multi-class Intelligent Traffic Detection system is developed. Difficulty (fire, accident, busy and sparse traffic) (fire, accident, dense and sparse traffic). The suggested method makes use of a CNN algorithm that effectively labels input images. First-pass analysis of congestion pictures is stored in the local buffer station. The final outcome is the addition of the spatial and temporal values.



As shown in Fig. 2 below, a 2D convolutional neural network

A schematic representation of a 2D convolutional neural network is seen in Fig.2 above.

Specified in the next subsection.

Specifically, our implementation includes the following modules:

- Dataset collection
- Image pre-processing
- Training using Convolutional 2D neural network
- Recognition
- Traffic condition intimation through Fast2sms

1. Dataset Collection
The internet is mined for a dataset of contrasting classifications to use as input. The acquired dataset is shown with an evaluation of the output class. Four each folder used for training and validation (sparse traffic, dense traffic, fire, accident) has 900 photos. Classifying output is represented by the folder name.
2. Image Pre-Processing
The "flow from directory" function in keras takes as input a training and test dataset that has been separated into several directories. With this, we are able to important preparatory steps like reducing the dimensions. The supplied image's dimensions are shrunk before being transformed to a Jumpy array.
Model A. Sequential Models in Keras come in both Sequential API and Functional API flavours. Modeling in sequence is Dependable for use in large-scale machine learning systems. The consecutive layers are simply loaded in a descending sequence. In the first line of the code, the model type is defined to be Sequential ().

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Layer B: 2D Convolutional Neural Network the 2D convolutional layer consists of a Conv2D ( ), kernel size, and a ReLu function, and it is used to process the 2D input picture. The Conv2D () layer, which includes the aggregate of output channels, is in the centre of the argument. The size of the sliding window and the strides may be set by adjusting the kernel size. The activation function is Rely. Finally, the size of the input layer is used to model it.

Layer C: 2D Max-Pool Added Include a max pooling layer in two dimensions. We estimate the pooling size to be (2, 2) in both the x and y axes for maximum precision. Then, include an additional n-channel convolutional and max-pooling layer. For the purposes of the Conv2D () function, the stride parameter is assumed to have the default value of (1, 1). It is used in keras as a means of balancing out pool sizes. The input tensor layer is provided the picture size and the number of output channels from the previous layer.

D. Level off and put a thick coating

In order to have a completely linked layer at the output, the layers are flattened. The flattening layer has two functions: dense () layer and soft-max. The layer density is the size parameter. The system uses 1,000 nodes to provide this level of size detail. All of the nodes have been set to ReLU. The total number of classes in the output layer may be specified using soft-max.

3. Training neural network

To train a network, we create a loss function or a certain kind of optimizer.

You may think of (keras.losses.categorical cross entropy) as a measure by which to compare and categories various types. Adam (keras.optimizers.Adam) is the optimizer of choice. When you call evaluate () on your model, that's when the metric is computed. The training process consists of the following four steps:

One is to use the x-train and y-train parameters to send the training data set in both directions.

Second, deciding how many items would be produced at once.

Specifying the total number of training iterations.

In order to get more information about how the training data set is doing, we may set the verbose option to 1.

4. Recognition

In order to recognize the class, the input picture is first transformed to a jumpy array, and then the array is compared to a trained model to get a classed output. Fires, accidents, and heavy or light volumes of traffic.

5. Detailed Design

Sample data labels may be seen in Table 1. Convolutional neural networks (CNNs) of five layers were employed in this round of testing. A five-layer Convolutional Neural Network (CNN) model is employed in the testing phase, and Rely Optimization comprises of one convolutional layer, one max pooling, and one Flatten layer.

Table1. Sample data representation of labeling

Layer Type	Layer operation	No of feature images	Feature map size	Validation steps	Total parameters
C1	Conv2D	900	150X 150	300	900

A. Algorithm Design

Size (in pixels), number of validations, channels, and total number of pictures are all Input Image Parameters. The picture is preprocessed by having its centre cropped and its aspect ratio determined.

Scaling: The Image is scaled by 150X150

Structural Design:

Number of Layers

Number of Neurons in each Layer

Regularization Parameters

Learning Rate

Dropout Rate

Weight Sharing

Activation Function (ReLU)

Algorithm for Weight Changes (SGD, Adam) based on a Divergence/Loss Measure (MSE, Cross Entropy, Binary Cross Entropy) RMSProp…) Towards a Sequential Model of Keas A Layer by Layer model is required to generate the Sequential Model API, however models that share layers or have numerous inputs or outputs are not supported.

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B. Trying out All test cases are put through their paces and bugs are fixed throughout the testing process. Each component undergoes its own set of tests after going through this procedure.

6. FAST2SMS

With the help of Fast2SMS, an internet service, Python can now send text messages.
Here is how the Fast2SMS API works:
To use Fast2SMS, just add the relevant mobile numbers.
Once you've registered your cell phone number, you'll be able to use it together with your password to sign up for Fast2SMS. In other words, a key for accessing the API will be provided. The Python code comes with both the authorization key and the accompanying cell phone number. The result, along with the time and date, will be texted to the cell phone number provided upon registration.
Using the Current Method vs. the Suggested Method Existing methods call for a substantial quantity of hardware equipment to be installed along the highway. As a further downside, they are very vulnerable to background noise and weather changes. Smaller datasets benefit from its improved accuracy, while it struggles with larger ones. The problems with the conventional approach are solved by the new one. Now that everything is digitized, fleet management can finally take off, thanks to deep learning. The CNN may be used to tackle Multiclass issues, which is an improvement over the current technique. This allows for rapid identification and dissemination of relevant data to the public.

V. RESULT

A convolutional neural network equipped with the input parameters specified in "Detailed design" is used to perform the experiment. Training complete, result achieved, our model is evaluated using a dataset of 200 photos for each type. Our model is around 80% accurate, as shown by experimental results. A 20th epoch is employed, and as seen in Fig. 4, the accuracy improves with each successive epoch.

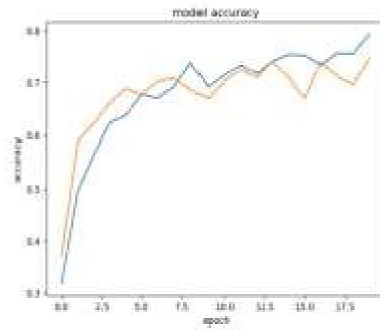
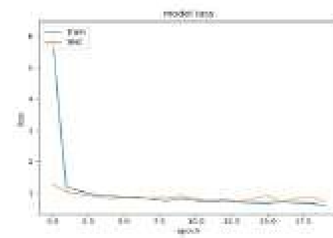


Figure 4: Reliability of the Model

Fig. 5 depicts the model loss in our experimental setup.



5 Models Predictive Error Diagram

Figure 6 depicts the screen that appears when the dataset is put into the programmed for training purposes.

Video and Image Traffic Forecasting Fig.6

Figure 7. Twenty-epoch dataset training.

Figure 7 shows the training of the dataset across 20 iterations.

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Figure 8: Congested Roads

Above, in Fig.8, is the expected output that has been placed on the picture, which demonstrates considerable traffic. Specifically, Fig.9 represents the image's integrated prediction depicts a lack of foot activity.

Fig. 9.low traffic output

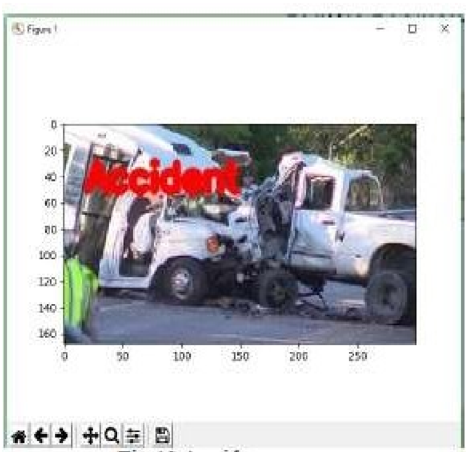

Figure 10: Results of Accidents

Above, in Fig.10, you can see the embedded prediction of the final product, which depicts a road accident.

Case in point 11: Output from a Fire Incident
Figure 11 displays the expected result, which depicts a fire accident.

VI. CONCLUSION

Congestion on the roads may be detected automatically without the need for human intervention by using a Convolution neural network. This is planned for implementation using deep learning for a wide range of practical purposes. The suggested CNN is treated as a multi class issue during training and validation.
Advances for the Future As a potential upgrade, traffic conditions might be identified in real time on traffic videos. To do this, one should just examine the traffic situation in each individual frame and use a suitable video splitting approach. Research on the feasibility of real-time video traffic detection is particularly crucial for emerging economies like India.

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