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Sensor Fusion Algorithms for Vehicle Classification based on Deep Learning

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Abstract: The deep learning is a growing multi-layer neural network learning algorithm in the field of machine learning in recent years. Firstly, analyzes the superiority of the deep learning at the aspect of feature extraction. Aimed at the lack of feature expression capacity and curse of dimensionality results from excessive feature dimensions of shallow learning, this proposes that using deep learning can extract high lever features from low-lever features though its given layer structure. Secondly, the deep learning algorithm is applied in the case of road vehicle detection. Based on the traditional method, such as neural network, the deep learning structure is further studied to increase the performance of feature extraction and classification recognition. Also, some tests are run in the MATLAB software. The tests results show that with the increasing the amount of the data, the mean error and misclassification rate gradually decrease, so this algorithm based on the neural network has good superiority and adaptability of the deep learning. Finally, this proposes some suggestions for the improvement of the algorithm and prospects the development direction of the deep learning in the field of machine learning and artificial intelligence.

Keywords: Deep learning, feature extraction, classification, vehicle detection, accuracy and loss

I. INTRODUCTION

Improvement of machines that can copy human exercises has for some time been sought after. Some of the time it is so as to improve the genuine nature of execution itself and by and large cost viability, on different events to liberate individuals from troublesome jobs i.e., tedious, work escalated work, or errands conceivably connecting to high dangers on wellbeing and security of faculty. Acoustic, seismic, and attractive sensors are regularly utilized to recognize and characterize ground vehicles because of their less limitations for situations where optical/radar-based sensor frameworks are inhibitive.

One model is computerized vehicle discovery and acknowledgment, and a framework that bolsters the assignment of vehicle identification and acknowledgment is considered here: for insurance of lives as well as an instrument to improve foundation security.As on account of identification of moving toward vehicles by people, and adequately assembling accessible data of the environmental factors, for example input signals, is the main noteworthy and critical assignment to be finished in acknowledgment forms.

Interruption by a moving vehicle quite often causes certain aggravation in the close by condition: in particular warm, seismic, acoustic, electrical, attractive, substance, and optical. In this manner, rather than human detecting, an assortment of detecting strategies has been created in computerized vehicle discovery to record such disturbance brought about by the objective vehicles, subsequently to identify the interruption.

An expanding interest can be seen in the vehicle arrangement issue in conveyed systems over the most recent two decades. Numerous strategies have been proposed to improve the arrangement execution. These investigations center for the most part either around extricating new highlights or adjusting the notable characterization calculations to various circumstances in design grouping assignments. For highlight extraction, both recurrence area and time-space strategies are proposed.

A. Objectives

Objectives of the project work are as follows:

1) Analysis of data fusion algorithms
2) Design and implementation of data level fusion
3) Design and implementation of automatic feature extraction algorithm
4) Classification of vehicles as AAV or DW

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II. METHODOLOGY

Figure 1 represents the methodology for the work implemented. The methodology is described in the steps shown below.

1) *Step-1:* The information at various hubs is gathered from two sensors specifically acoustic and seismic
2) *Step-2:* Automatic extraction is done on the informational index to execute information level combination to accomplish multimodal vehicle characterization
3) *Step-3:* This undertaking executes LSTM model to accomplish the abovementioned and think about the consequences of manual and programmed highlight extraction
4) *Step-4:* The element maps are then progressively convolved and went through pooling layers
5) *Step-5:* Various parameters like confusion matrix training session graph to compare the performance of the models on time series data obtained from sensors
6) *Step-6:* To compare the accuracies in different feature extraction methods

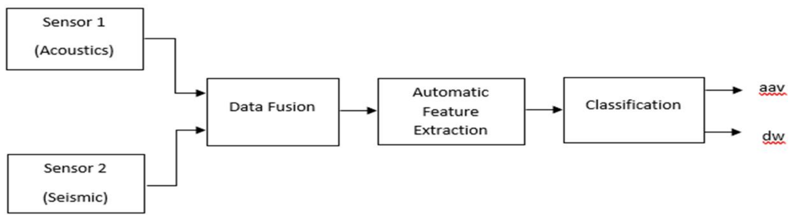

Figure 1: Flow diagram of the methodology implemented

III. RESULTS AND DISCUSSION

A. *Accuracy and Loss*

An epoch denotes one cycle through the full training dataset. Typically, training a neural network requires more than a few epochs. In other words, if we feed a neural network the training data for more than one epoch in different patterns. As shown in the figure 4.1 epochs till 50 were conducted and the efficiency showed drastic change from 30% to 87.3%.

For the learning rates 0.005, 0.0001, 0.0005, the accuracy for processed data is calculated. This depicts that the accuracy of the model increase as the learning rate is decreased for training.

The accuracy and the loss for the processed data for different training to testing ratio. The learning maintained during this is 0.00005. The ratio of training and testing samples have been varied and model is trained and evaluated for 50-50,60-40,70-30,80-20.

Table 4.3 Accuracy for various train to test ratio

Training to testing ratio	Accuracy achieved
80-20	86.70%
70-30	82.40%
60-40	80.30%
50-50	78.20%

B. *Training Session Plot*

As shown in the figure 4.1, training accuracy and train loss is shown over the batch of epochs ranging from 1 to 50. The loss calculation is done using cross-entropy method for the training.

Training on single CPU.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	1	00:00:00	0.29	4.3e-02	1.0000e-04
50	50	00:00:00	0.20	2.0e-02	1.0000e-04
100	100	00:00:01	0.11	6.1e-03	1.0000e-04
150	150	00:00:02	0.09	4.2e-03	1.0000e-04
200	200	00:00:02	0.07	2.8e-03	1.0000e-04
250	250	00:00:03	0.06	1.9e-03	1.0000e-04
300	300	00:00:03	0.06	1.6e-03	1.0000e-04
350	350	00:00:04	0.05	1.5e-03	1.0000e-04
400	400	00:00:04	0.05	1.4e-03	1.0000e-04
450	450	00:00:05	0.05	1.4e-03	1.0000e-04
500	500	00:00:06	0.05	1.4e-03	1.0000e-04
550	550	00:00:07	0.05	1.3e-03	1.0000e-04
600	600	00:00:08	0.05	1.3e-03	1.0000e-04
650	650	00:00:08	0.05	1.3e-03	1.0000e-04
700	700	00:00:09	0.05	1.2e-03	1.0000e-04
750	750	00:00:09	0.05	1.2e-03	1.0000e-04
800	800	00:00:10	0.05	1.1e-03	1.0000e-04
850	850	00:00:10	0.05	1.1e-03	1.0000e-04
900	900	00:00:11	0.05	1.1e-03	1.0000e-04
950	950	00:00:11	0.05	1.0e-03	1.0000e-04
1000	1000	00:00:12	0.04	9.9e-04	1.0000e-04

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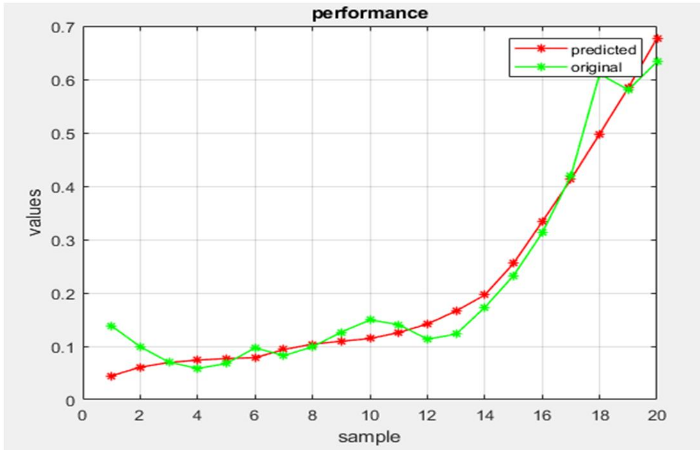

Fig 3.1 Training session's progress over iterations

The proposed method in mainly at feature extraction level. Here, we used both time-domain and frequency-domain features. As frequency-domain features, we estimated spectral densities. However, instead of using the DFT of the signals as features directly, we analyzed the spectral density of the training data and then determined the discriminative frequency bands. As we show in the following subsections, this approach increases the effectiveness of the frequency-domain features, i.e. causes an increase in the classification performance and a reduction in the false alarm rates. It is also worth mentioning that this approach yields a very small number of features.

C. Confusion Matrix

A disarray network (Confusion Matrix) is a conservative depiction of figure results on a portrayal issue. The amount of right and wrong conjectures is summarized with check regards and isolated by each class. This is the route in to the chaos matrix. The chaos cross section shows the way the course of action model is perplexed when it makes desires. It gives us understanding not simply into the goofs being made by a classifier anyway more basically the sorts of slip-ups that are being made. The confusion framework for vehicle portrayal is given by Fig 4.2.

Meaning of the Terms:

1) Positive (P): Observation is certain.
2) Negative (N): Observation isn't certain.
3) True Positive (TP): Observation is certain, and is anticipated to be sure.
4) False Negative (FN): Observation is certain, however is anticipated negative.
5) True Negative (TN): Observation is negative, and is anticipated to be negative.
6) False Positive (FP): Observation is negative, however is anticipated positive.

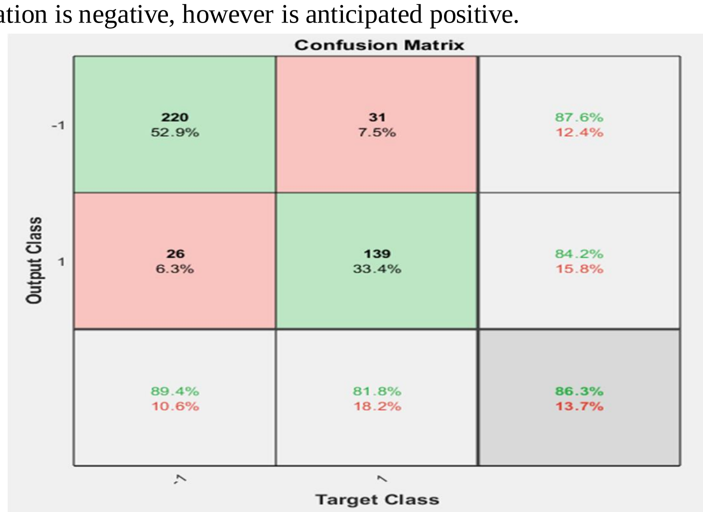

Fig 4.2 Confusion matrix for Vehicle Classification

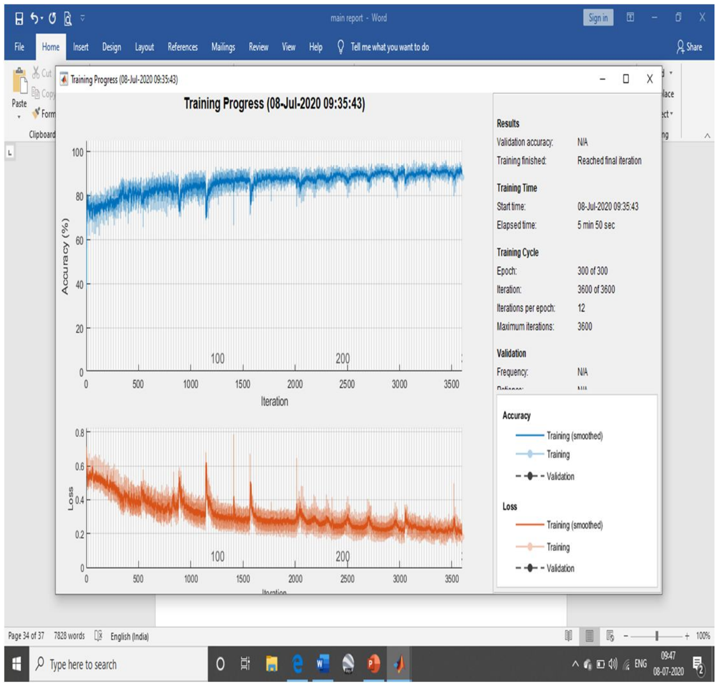

Fig 4.3 Training progress of the vehicle classification.

The above fig 4.3 shows the training progress of the vehicle classification. In the tests, the data set is randomly divided into two parts in which one is a training set of 80% and the remaining 20% of data is a testing set for verifying the algorithm effects. Feature extraction method before vehicle detection classification, the accuracy rate of vehicle detection classification will increase.

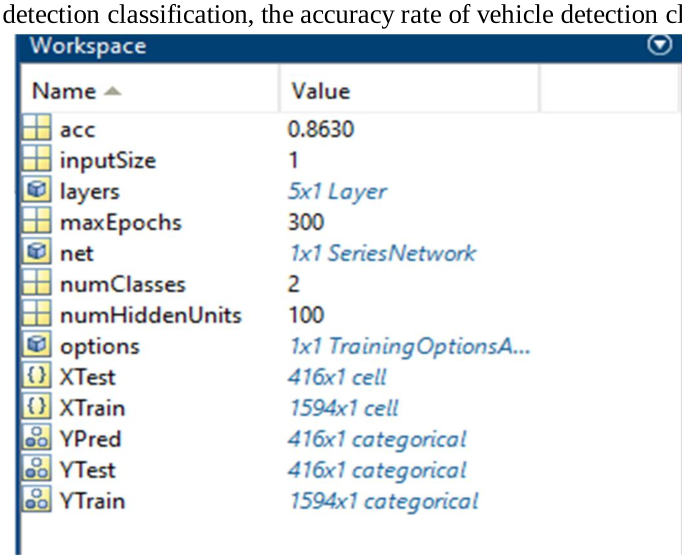

Fig 4.4 Classifications parameters of vehicle classification

As in the fig 4.4 we are achieving the accuracy of 86.3%. The loss is 13.7%.

IV. CONCLUSION

Conclusion from this project is that vehicle classification might play an important role in developing security infrastructure in our society. The potential of using deep learning models is realized in the project. The acoustic and seismic sensor data are fused at data level and efficiency up to 87.3% is achieved in this project. The LSTM model was found to fit more accurately on this dataset rather than machine learning models such as KNN and SVM. The proposed methods can learn features from raw data through the deep layer structure of LSTM with fewer requirements of expert knowledge or human labour for feature extraction and fusion level extraction.

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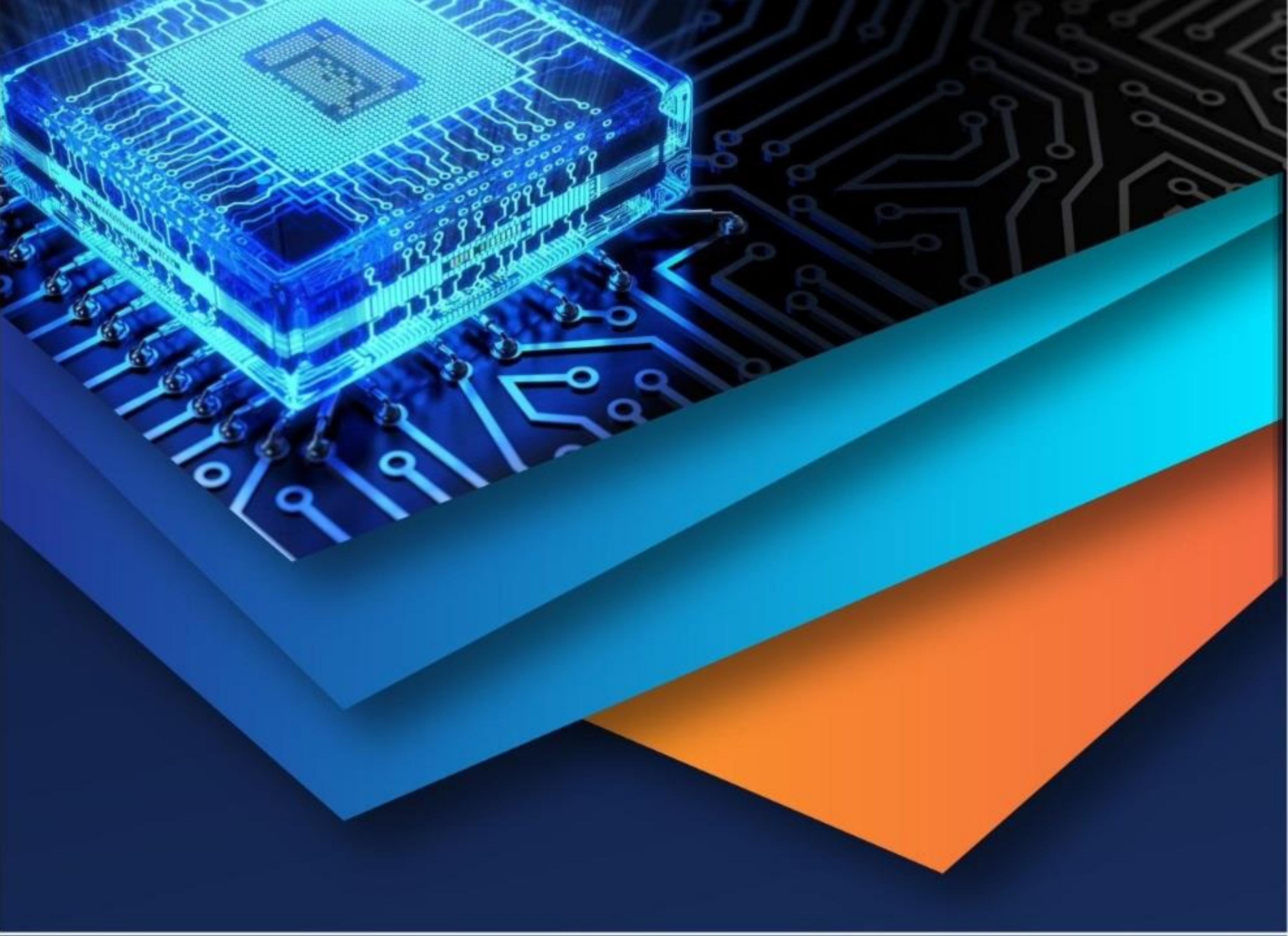

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