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MACHINE LEARNING – AUTONOMOUS VEHICLES

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Abstract

Machine learning is a technique that can be used for making machines aware of their environment. This research has presented a comparative analysis of the supervised and the unsupervised learning models and the various patterns used in the classification of the models. The two learning models affect the attainment of real Artificial Intelligence. The research further provided data on an ideal case of machine learning where an algorithm was used to evaluate the accuracy of the learning models as the effect on the car steering angle.

Keywords: Machine Learning, Deep, supervised, autonomous

1. Introduction

The machine learning and autonomous vehicles have become key technologies in our daily lives. The driving of a car and maintaining it on the road is a simple task for human beings. Artificial intelligence is used for the solution of the complex tasks that utilized high dimensional data as the input. The construction of the sophisticated agents that are capable of driving cars is still in infancy. The task to create this human-like performance is still a difficult task [1].

The autonomous driving cars have always been an element of research for the last decade and will continue to be a point of interest in the foreseeable future. The development of the Advanced Driving Assistance Systems (ADAS) is a project that is still an ongoing process since the inception of the digital car [2]. The development commenced in 2000, but the development has accelerated since then leading to the development of the cruise control, blind spot indicators, automated parking, intersection assistance, collision protection system, traffic sign recognition system and driver monitoring system.

The applications utilize a huge amount of information for normal operation such as the data from sensors such as lidar, radar and camera. The sensors generate their respective data in large amounts. Thus, huge dimensional data require sophisticated methods to handle the data. The machine learning (ML) provides various approaches that can be utilized in the solution of the problem [3]. The Machine Learning provides the Deep Learning (DL) approach that extracts pertinent features from the high-dimensional data. The task is accomplished with a function-approximator which utilizes multi-layer computational graph known as Neural Network. The use of Neural Networks has increased tremendously in the recent years. The technology is currently used in the automotive field.

Presently, most companies that are developing autonomous vehicles are using deep learning to create computer vision, i.e. a perception layer that will permit the vehicles to comprehend what it sees. The annotated data is the best for deep learning in autonomous vehicles [1]. The approach utilizes a rule-based approach to the creation of the path plan and the driving action for the vehicle once it comprehends what it sees. The result of such an approach entails the anticipation of definite numbers of edge-cases across the layer of the self-driving stack. The rule-based approach is limited by the fact that it cannot understand and drive in a completely new environment like humans [3].

Thus recently deep learning techniques have been employed as functions of approximators in Reinforcement Learning (RL) models, resulting in a deep Reinforcement Learning [4]. The reinforcement learning unlike the DL techniques which are based on a trained labeled dataset, the models are trained by an interacting environment [2]. The primary objective of the RL-model has been in the finding of an optimal behavior, via the exploration of the environment using an iterative method [4]. The deep reinforcement learning models have been utilized in games such as the ancient game of Go and the old Atari games. There has been a lot of advancement in the field of artificial intelligence promoting the development of continuous control of a reinforcement learning method [4]. The application of the algorithms has been successfully applied in the MujoCo physics engine which has illustrated good results. The application in the game engines has acted as a benchmark for the reinforcement learning algorithms.

The key drawback of deep learning is that the networks require an enormous amount of data. The problem is compounded and made worse by the factor that the methods that exist for data augmentation cannot generate sufficient large datasets [2]. The current research field is made of the use of synthetic data for training machine learning algorithms. In the case of autonomous vehicles, the acquisition of eth training data is a difficult task as the data can be biased by containing data from the ideal driving conditions [1]. The training of the model on synthetic data can be used as a remedy for the problem. The synthetic data can be used in the creation of non-ideal driving conditions and scenarios. The training on synthetic data will boost the reinforcement learning model as the algorithms in the model require the interaction of agents in an environment in an iterative manner [2]. The RL-model allow autonomous vehicles to learn by exploring the environment and the various actions; thus, training using real conditions, in this case, is still improbable as there are chances of accidents occurring in the setting [4].

Theory

Machine Learning

Machine learning is a data analysis technique that automates the analytical model building [5]. Machine learning is a division of artificial intelligence that rely on the fact that systems can learn and be trained from data, identify significant patterns and make decisions while reducing human intervention [5]. Machine Learning (ML) was introduced as a concept in Artificial Intelligence. ML was introduced as a concept that is used in the teaching of machine different patterns and the adaption of new circumstances [5]. Considering learning and decision making is a core level of the arguments in biological being then it will be employed in artificial intelligence. The machine learning process can either be experience or explanation-based learning. Machine Learning is a crucial element in robotics as it assists in optimizing decision making for machines that eventually leads to increment in the efficiency of the machines and the organization of the various tasks. ML has become a core concept in intelligent systems that can contribute to innovating technology in autonomous systems [6].

Learning is an element of intelligent machines. Deep learning would help in the making of decisions especially in optimize learning to ensure efficient operational methods. The use of ML has made the making of heavy machinery and their control easier. Explicit algorithms have been introduced so assist in the understanding of the virtual environment and subsequently make the right decision [6]. The algorithms decrease the quantity of the programming concepts that are used while making the machines independent, i.e. autonomous leading to making their decision. They machine learning algorithms can be classified as either supervised or unsupervised based on the way they “learn.”

Supervised Learning

This is the most common machine learning algorithms. The technique entails the linear, multi-class classification, support vector machines and logic regression algorithms [7]. The supervised machine learning is named so as the data scientist will guide the teaching of the algorithm as to the conclusion that it should come up with. The algorithms in the supervised learnig have predictable outputs. The data employed in the training of the machines is always labeled with the expected correct answers. For instance, a classification algorithm will learn to identify animals and provide a label of their species using some identifying characteristics [8].

Supervised learning is based on training a data sample from data sources using a classification in which the answer is already assigned. The technique has been largely used in Multilayer Perceptron (MLP) and feedforward model [8]. To put into perspective, the MLP has three distinctive features;

- The presence of hidden neuron layers that is not part of the input or the output layers in the neural network. These layers allow the network to easily learn and solve all the complex tasks associated with the machine.
- The non-linearity witnessed in the neuronal activity is easily differentiable.
- The interconnection model of the network reflects an increased degree of connectivity.

The above features and the ability to learn via training will increase the capability to solve difficult and diverse tasks. For instance, the supervised leaning using the ANN model is referred to as error back-propagation algorithm [8]. The error correction-learning will train the algorithm on a network-based system of input-output technique especially in the finding of the error signal [7]. The error signal is computed via the calculation of the difference between the output and the desired output. The error signal will be used in the adjustment of the synaptic weights of the neurons in proportion to the error signal [8]. The error propagation in supervised learning can occur in the following phases.

Forward pass

Starts with the presentation of eth vector to the network. The input signal in the network will be propagated forward in the neuron by neuron fashion. The signal is propagated via the network while emerging as an output at the other end.

$$y(n) = \varphi\big(v(n)\big)$$

Where

$v(n)$ is the induced local field of the neuron that can be illustrated as:

$$v(n) = \sum w\,(n)y(n)$$

The output will be computed using the comparison of the desired response d(n) and the error e(n) for the neurons at the output layer o(n). The synaptic weight in the case of the forwards pass will remain the same [8].

Backward Pass

The error, in this case, will come from the output neuron which will be propagated backwards via the network [7]. The task will lead to the computation of the local gradient for the various neuron in the layers leading to the change in the synaptic weights of the network [8]. The variations in the synaptic weight in the network will occur following the delta rule

$$\Delta w(n) = \eta \ x \ \delta \ (n) \ x \ y \ (n)$$

The recursive calculation in the above computation especially in the forward pass then followed by the backward pass to ensure that each input pattern in the network converges [8]. The supervised learning increases efficiency in the ANN algorithm especially in the determination of solution for linear and non-linear problems such as the algorithms used in forecasting, prediction, plant control, robotics and classifications [8].

Unsupervised leaning

The unsupervised machine learning is also referred to as the true artificial intelligence. This kind of learning is where the computer can learn to identify the complex processes and the associated patterns without human aid or guidance [8]. The unsupervised machine learning is prohibitively complex for conventional enterprise use, but it opens up the avenues for the solving of problems that humans would not traditionally tackle [7, 8].

In the case of the unsupervised learning, there is the input data (X), but there are no corresponding output variables [9]. The fundamental goal of the unsupervised learning is the ability to model the underlying structure or the distribution of the data while learning more about the data. The basic structure of the unsupervised learning is that there are no correct answers in the learning process and there is no human or machine teacher [9]. The algorithms are left to learn on their own while discovering and presenting data in its interesting structural form.

The unsupervised learning combines, all the learning into the following classifications:

- Cluster: The clustering of problems entail the discovering the inherent groupings in the data like the evaluation of the grouping of the customers by their purchasing behavior, e.g., the k-means algorithm for clustering problems [9].
- Association: The association rule in the unsupervised learning problem entails the description of the rule that describes a greater portion of any given data, e.g., the Apriori algorithm for the association rule machine learning problems [9]. Other forms of algorithms are principal and independent component analysis [9] and association rules.

The self-organizing neural networks learn via the use of unsupervised learning algorithms. The algorithms are used in the identification of the hidden patterns in the unlabeled input data [8]. The unsupervised technique refers to the ability of the machine learning and organizing information without the generation of an error signal that will be utilized in the evaluation of the potential solution [8]. The lack of direction in the learning of the algorithm is unsupervised which can be beneficial sometimes [9]. The algorithms in the unsupervised learning permit the evaluation of the patterns to determine the errors in the system. The self-organizing Maps (SOM) has the following characteristics

The incoming signal pattern will be transformed into a one or two-dimensional map. The transformation will be executed adaptively.

The network utilized in this system will represent a feedforward structure that will have a single arithmetic layer made of neurons that are set in rows and columns [9].

The stages in the representation will ensure that each of the input signals is in a proper signal.

The neurons working closely with the associated pieces of information will ensure communication via synaptic connections [7].

The computational layer is sometimes referred to as the competitive layer due to the competition between the neurons [8]. The algorithms in the unsupervised machine learning are also referred to as competitive algorithms. The unsupervised algorithms occur in three phase in the self-organizing Maps (SOM) [5].

Competition phase

Considering the input pattern x, which is fed to the network then the internal product assigned the synaptic weight w will be computed and the neurons in the competitive layer will find s discriminant neuron that will spark competition among the other neurons, and the synaptic weight vector that will be associated with the input vector based on the Euclidean distance will be considered the winner [8]. The winner neuron, in this case, will be referred to as the best matching neuron i.e.

$$x = \arg\min ||x - w||$$

The Cooperative phase

The wining neuron will verify the center of a topological neighborhood termed as h for the other cooperating neurons [6]. The computation will be performed using eth lateral interaction parameter d in the cooperating neurons. Once determined the topological neighborhood will be reduced in size over time [7].

The Adaptive phase

The best matching neuron and the associative neurons will increase their values, i.e., for the discriminant function with regards to the input pattern via an appropriate synaptic weight adjustment shown in the equation below [8].

$$\Delta w = \eta h_{(x)}(x - w)$$

When evaluated multiple times the training pattern, then the synaptic weight vectors will seem to comply with the distribution of the input patterns because of the surrounding updating and the ANN will be learned without supervision [3].

The robustness associated with the SOM models is that the neurons will possess the actual neuro-biological behavior; thus, it is applied in most real-world application such as texture segmentation, clustering, speech recognition and vector coding [9].

Challenges

Machine learning is making significant development in cybersecurity and autonomous cars, and this section will endeavor to evaluate the various challenges that face the development of the technology [10]. The challenges identified in this case have hindered the full attainment of autonomy courtesy of machine learning.

Memory networks

The memory augmented neural networks in machine learning still required huge working memory for the storage of data [10]. The network requires the connection of a memory block that permits read and writing by the network [10]. For the attainment of true efficient and effective AI, there is the need for the network to have access to a seamless method of storing and accessing data when required.

Natural Language Processing (NLP)

Despite all the efforts put in the attainment of a natural machine language, there is still a long way to the creation of a natural language processing and comprehension of language. The problem is still profound even for the deep networks [10]. The current practice entails machines being taught to represent language and then taught based on the representation [10]. The simulation techniques have consistently provided poor techniques.

Attentions

The human biological systems utilize attention in a highly robust manner to integrate sets of features [10]. The current practice in machine language focuses on small chunks of the input stimuli, stepwise while integrating the results at the end [10]. There is the need of the integration of the human-like features into the neural networks especially in responding to the stimulus and the access of the memory block. In reality, the attention in the system is meant to be non-differentiable [9].

One-Shot Machine Learning

The current machine learning has come a long way especially the applications of the neural networks [11]. The conventional gradient-based networks require enormous amounts of data for learning accomplished using extensive iterative training [11]. The one-shot learning entails the neural networks learning via a single example reducing the amount of data stored.

Comprehension of the deep nets training

Most professionals have little or no knowledge of the operation and functioning of the deep nets training [10]. There is need to understand the working of the deep nets to continue making progress in the attainment of autonomy [9].

Video training data

The traditional machine training entails the use of static images rather than video training [10]. The enhancement of the machine learning of various systems will be achieved via listening and observing [11]. The video datasets provide a wider variety of information compared to the static images.

Object detection

Object detection in machine learning is still a complex feat to achieve especially considering that the algorithms cannot correctly identify the images due to lack of the classification and the localization of the computer vision in machine learning [11].

Classification

Classification is a common decision-making problem that occurs when there is need to group or put objects in a class using a variety of observed features and attributes [8]. There numerous industrial problems that are considered classification problems such as medical diagnosis, prediction of bankruptcy and stock markets, character recognition, weather forecasting and speech recognition. Non-linear and arithmetic methodologies can be used in the solving of classification problems [9]. When solved mathematically there are the issues associated with the accuracy and the distribution of data properties and model capabilities [8].

The ANN algorithm has been proven as an excellent classification model as it is non-linear, adaptive and functional approximation principles [10]. The algorithm, when used in a neural network, will classify the objects based on the output activation [9]. In machine learning programs a set of input patterns are used in the network hence the hidden layers in the network will be used in the extraction of the features of the patterns in the system [9]. When used in a two hidden layers ANN model, the hidden nodes in the in the first layer will be the boundary between the patterns classes and the hidden nodes in the second layer [10]. The nodes in the second layer will be decision region of eth hyper planes formed in the previous layer. The layers can be combined with the decision layer to form class 1 and class 2. The classes will be determined by the training errors. The classification in SOM is effected by the extraction of features and then transforming the m-dimensional input to q-dimensional feature output this will also be vital in the grouping of the objects in accordance to the input pattern [11].

This study is vital as it wil present the conceptual difference between the supervised and the unsupervised framework. The evaluation will entail the utilization of a known learning algorithm. The differences will be highlighted and compared with their application in the autonomous vehicles.

2. Research Method

The data collection mechanism entailed the automated testing methodology for the autonomous cars that will be critical in answering the following questions:

- Which means is recommended for the exploration of the input-output spaces of an autonomous vehicle?
- How can realistic inputs be generated to be used in the automation of the results?

Data Collection

The input-output space of complex systems such as the autonomous vehicles is generally large for exhaustive exploration. To fully explore these systems there is the need to systematically partition the space into different classes that are equal and evaluate each class by taking samples from the classes developed. The neuron coverage will be used as a partitioning mechanism. The coverage will partition the input based on the assumptions in the inputs.

The testing of the Neuron coverage

The initial neuron coverage was proposed by Tian et al. (2017) to act as a guidance for the testing of the differential testing of multiple [12]. The neuron coverage is defined as the ratio of the neurons activated for any particular input and the total number of neurons in the system.

$$Neuron\ coverage\ =\ \frac{|Activated\ Neurons|}{|Total\ Neurons|}$$

A neuron is considered activated if the input is greater than the Deep Neural Network (DNN) threshold. In this case, it was considered as 0.2. The output of the various layers was compared for instance those neurons that are located in the fully-connected layers then the results will be compared directly using their inputs against the neuron activation threshold. The neuron in this layers has a single scalar value. The neurons in the convulsion layer have an output that has multidimensional feature maps. For example, a test can be carried by applying a convolutional kernel size (3x3) to the entire image (5x5) leading to the production of a feature map of size

(3x3) in the succeeding layer. The average of the output future map will be used in the conversion of the multidimensional output of the neuron to the scalar values then compared with the neuron activation threshold as illustrated in the image below

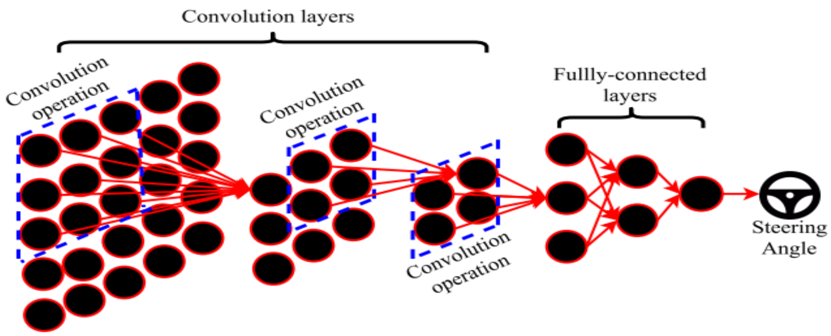


Figure 1: The simplified deep neural network (DNN) learning for the autonomous vehicle.

In other cases, the neurons can be considered in the recurrent neural network where the loops will be unrolled to produce the sequence of the outputs. As illustrated below in figure 2.

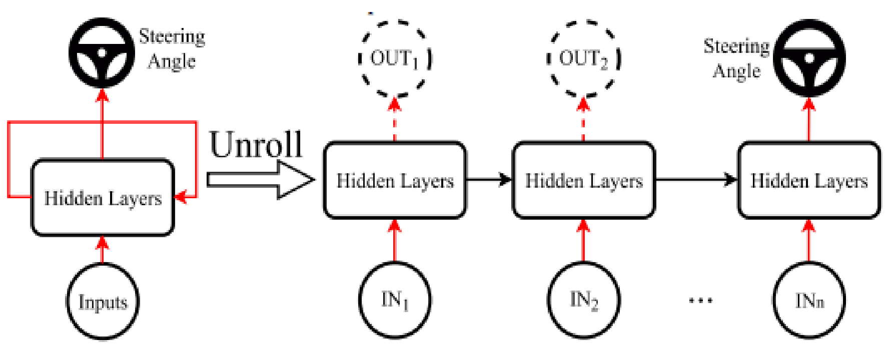
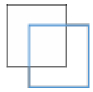
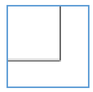
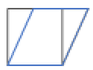
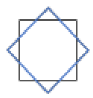


Figure 2: The simplified recurrent neural network (RNN) learning for the autonomous vehicle.

The increment of the coverage using the synthetic images

The use of arbitrary inputs, in this case, will be important in the maximization of eth coverage especially if there is the likelihood of the inputs appearing in the real-world. The deep test, in this case, will be aimed at generating realistic synthetic images by applying images that will mimic the real world. The key image formation phenomena that will be investigated in this research: varying contrast, varying brightness, translation, horizontal shearing, scaling, blurring, rain effect, rotation, and fog effect. The transformations can be classified into the following groups, i.e., affine, linear and convolutional. The affine transformation can be expressed in as a matrix

Table 1: The matrix used for the affine

Affine Transform	Example	Transformation Matrix	Parameters
Translation		$\begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix}$	t_x: displacement along x axis t_y: displacement along y axis
Scale		$\begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \end{bmatrix}$	s_x: scale factor along x axis s_y: scale factor along y axis
Shear		$\begin{bmatrix} 1 & s_x & 0 \\ s_y & 1 & 0 \end{bmatrix}$	s_x: shear factor along x axis s_y: shear factor along y axis
Rotation		$\begin{bmatrix} \cos q & -\sin q & 0 \\ \sin q & \cos q & 0 \end{bmatrix}$	q: the angle of rotation

The affine transformation can either be scaling, translational, rotation and horizontal shearing [12]. The affine transformation is vital in this exercise as it will be used for the linear mapping between two images for the preservation of the planes and the straight lines. The affine transformation is used in the correction of the distortion caused by the changes in the angle of the camera [12]. The affine transformation is used for the stimulation of the various real-world conditions

The other mechanism that is vital for the experiment will be the blurring and add fog/rain effects. The convolution will lead to the addition pixel of the input images to its local neighbors. The best techniques of blurring will be based on filtering schemes such as bilateral, averaging, median and Gaussian [12].

Autonomous Driving in Deep learning Network

The technic used in the evaluation of the result used literature from the three models that were utilized in the Udacity self-driving challenge [12]. The techniques were the Rambo, Chauffeur, and Epoch [12]. The techniques were selected as their application was easy based on the Keras framework. The test condition is illustrated in the table below.

Table 2: The DNNs for the evaluation

Model	Sub-models	Number of neurons used	Theoretical MSE	Experimental MSE

Chauffeur	LSTM CNN	513 1427	0.06	0.06
Epoch	CNN S1, S2, and S3	1625 3801 13473	0.06	0.05
Rambo	CNN	2500	0.08	0.10

Rambo

The Rambo technique has the three CNN s models that will merge the output on the final layers. The CNN is based on NVIDIA's self-driving model architecture [12]. This model's input is the difference among the three consecutive images [11]. The model is based on the Keras and Theano frameworks [12].

Epoch

Uses a single CNN architecture, the model entails training the autonomous vehicle using the instructions provided by the author [12]. The model utilizes the Tensorflow and the Keras frameworks [11].

Chauffeur

The model utilizes the CNN and the LSTM model where the former is used for the extraction of the image features whereas the latter is used in the predicting of the steering angle of the autonomous vehicles [12]. The Chauffeur uses the same framework as the Epoch.

The Image transformation

There were seven different image transformations used in the preparation of the images, i.e., scaling, horizontal shearing, translation, brightness adjustment, contrast adjustment, rotation, and blurring.

3. Results and Analysis

The DNN models are dissimilar to the conventional software as the process entails the evaluation of the neuron coverage which will be used for the illustration of the functional diversity of DNN. The test determined whether the neuron coverage variation based on the input-output pair of the autonomous vehicle. The output of each neuron will be passed via a sequence of linear and non-linear operations before being considered for the final output of the DNN.

Table 3: The relationship between neuron coverage and test output

Model	Sub-Model	Steering Angle	Steering Direction	
		Spearman Correlation	Wilcoxon Test	Effect size (Cohen's d)
Chauffeur	Overall	-0.10 (***)	left (+ve) > right (-ve) (***)	negligible
	CNN	0.28 (***)	left (+ve) < right (-ve) (***)	negligible
	LSTM	-0.10 (***)	left (+ve) > right (-ve) (***)	negligible
Rambo	Overall	-0.11 (***)	left (+ve) < right (-ve) (***)	negligible
	S1	-0.19 (***)	left (+ve) < right (-ve) (***)	large
	S2	0.10 (***)	not significant	negligible
	S3	-0.11 (***)	not significant	negligible
Epoch	N/A	0.78 (***)	left (+ve) < right (-ve) (***)	small

Data Processing

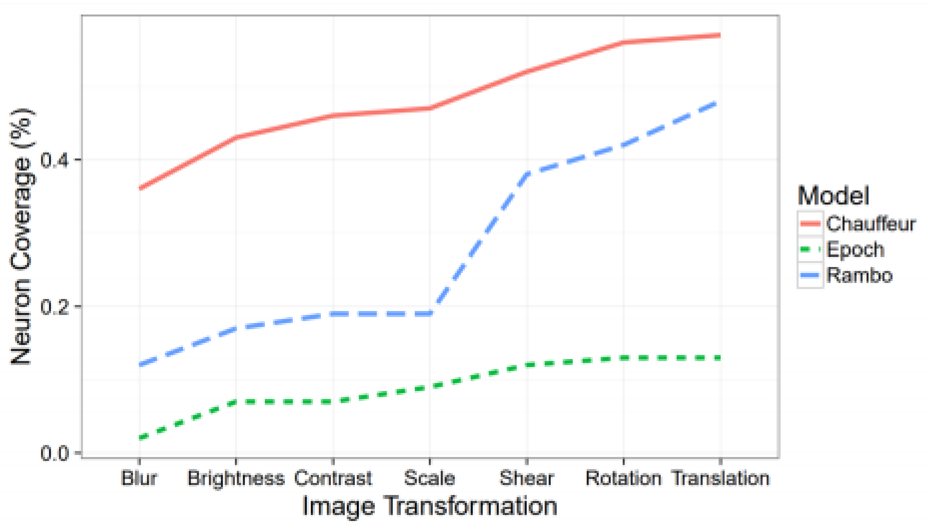


Figure 3: The cumulative neuron coverage per the input image

Table 4: The Neuron coverage basd on the image coverage

Transformation	Chauffeur (CNN,LSTM)	Epoch	Rambo (S1,S2,S3)
Scale	(1.0,0.0) (0.67%,0%)	39.0** 93%	(2.0*,5.0*,32.0) (0.41%,1%,4%)
Brightness	(100.0**,1.0) (67%,0.2%)	113.0** 269%	(67.0**,104.0**,585.0*) (14%,24%,66%)
Contrast	(120.0**,1.0*) (80%,0.2%)	75.0** 179%	(47.0**,100.0**,159.0) (10%,23%,18%)
Blur	(41.0**,0.0) (28%,0%)	9.0* 21%	(18.0**,23.0**,269.5*) (4%,5%,31%)
Rotation	(199.0**,2.0*) (134%,0.39%)	81.0** 193%	(70.0**,13.0**,786.5*) (14%,3%,89%)
Translation	(147.0**,1.0*) (99%,0.2%)	65.0** 155%	(143.0**,167.0**,2315.5**) (29%,38%,263%)
Shear	(168.0**,1.0*) (113%,0.2%)	167.0** 398%	(48.0**,132.0**,1472.0**) (10%,30%,167%)

Table 5: The increase in the neuron coverage

Model	Addition w.r.t baseline activation
Chauffeur-CNN	17 %
Epoch	22 %
Rambo-S1	12 %
Rambo-S2	21 %
Rambo-S3	0.5 %

Discussion

The neuron coverage is related to the input-output diversity hence can easily be utilized in the systematic test generation [3]. The test evaluated the neuron coverage for each input images. The neuron coverage was investigated for the following elements

Steering angle

The steering angle is described as a continuous variable in the neuron coverage. The measurement technique is a non-parametric measure used in the computation of the monotonic association between the two variables [7]. The results illustrate that the steering angle increases with the increase in the neuron coverage. The Rambo and the chauffeur models have a negative association while Epoch model has a positive association. There is a variety in the activation of the neurons and the output of the steering angles [11]. The neuron coverage is a robust technique for the approximation of the effect of the various input-output pairs.

Various image transformation in the test activated different sets of the neurons. The test entailed the evaluation of 1000 input images they were tested set and then transformed using the seven different transformations discussed earlier. The neurons are activated via the synthetic images. The dissimilarities between the neurons are measured using the Jaccard distance a sin the equation below

$$1 - \left|\frac{N_1 \cap N_2}{N_1 \cup N_2}\right|$$

The results demonstrate that all the models with the exception of the Chauffeur LSTM model that different transformations activate different neurons. The LSTM is different as it is an RNN-based architecture that maintains the state from the previous inputs so as to increase the neuron coverage [10]. The experiment further evaluated the contribution of the transformation to the neuron coverage, i.e., from T_1, T_2 …T7 will allow the calculation of the neurons activated i.e. $T_1, T_1 \cup T_2, \dots, \bigcup_{i=1}^{7} T_i$. From these computations, it is evident that all the transformation contributed to the overall neuron coverage [11].

The experiment also evaluated the effect of combining the images transformations on the neuron coverage. The experiment was based on a cumulative transformation there are various images that activated a different set of neurons hence the combination of multiple neurons will lead to increased activation of the neuron coverage [10]. The guided transformation was also utilized to investigate whether there is further increase in the cumulative neuron coverage using an algorithm. For the Epoch model has a cumulative percentage of 51% while the Rambo model had 64 %, 70 % and 98 % for the S1, S2, and S3 respectively. The Chauffeur-CNN model had a collective activation of 88% while the increment is illustrated in table 4. The systematic combination of the various image transformations illustrates an improvement of the neuron coverage.

The further evaluation of the results illustrates that the models also were prone to erroneous results especially based on the transformation of the input images [11]. The Rambo model has 23 cases or errors associated with the shear transformation while the other models had no errors. The use of the DeepTest illustrated more errors for the models. For instance, the Chauffeur model for the rain condition had 650 cases while the Epoch and Rambo have 64 and 27 cases of errors respectively [12]. It is evident that the DeepTest found more than 1000 erroneous behavior in the models. The use of the DeepTest can be used in the improvement of the accuracy of the DNN while retaining the synthetic data. The DeepTest was crucial in the predicting of the realistic performance of the models and the synthetic images. A DNN model for the handling of the autonomous vehicle should also control the braking and the acceleration of the car. The test evaluated the steering angle to verify the accuracy of the technique. The technique should be expanded to be able to accommodate the output of the working of the braking and acceleration when supported in the model.

Flowchart

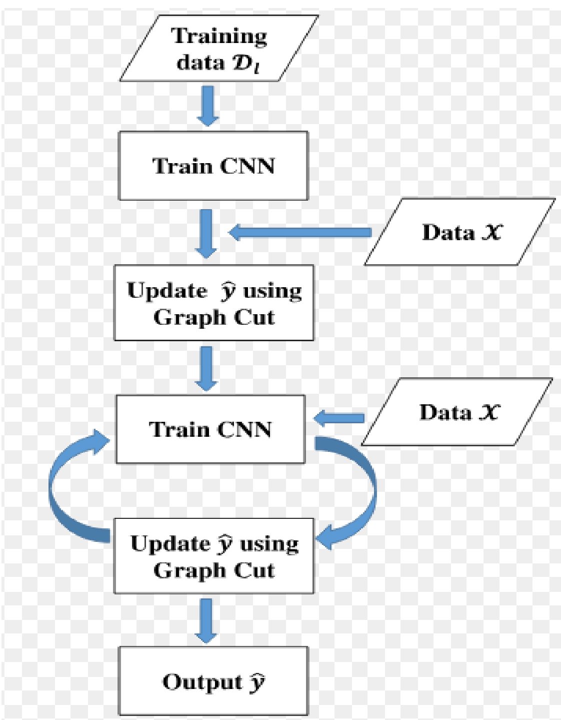


Figure 4: A flowchart showing the Machine training using the CNN algorithm

Sample algorithm

```
Push all seed imgs □ I to Stack S
genTests = φ
while S is not empty do
img = S.pop()
Tqueue = φ
numFailedTries = 0
while numFailedTries ≤ maxFailedTries do
if Tqueue is not empty then
T1 = Tqueue.dequeue()
else
Randomly pick transformation T1 from T
end
Randomly pick parameter P1 for T1
Randomly pick transformation T2 from T
Randomly pick parameter P2 for T2
newImage = ApplyTransforms(image, T1, P1, T2, P2)
if covInc(newimage) then
Tqueue.enqueue(T1)
Tqueue.enqueue(T2)
UpdateCoverage()
genTest = genTests ∪ newimage S.push(newImage)
else
numFailedTries = numFailedTries + 1
end
end
end
return genTests
```

Figure 5: A sample CNN algorithm

4. Conclusion

This research has been able to evaluate the machine learning techniques for the performance of the autonomous vehicle. An algorithm based test was carried out using the DNN-driven autonomous car. The learning technique was based on the use of images that were enhanced with synthetic images. The accuracy of the algorithm, as well as the errors associated, were evaluated using the DeepTest which is a tool for the test and automation of the DNN-driven.

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