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Driverless Cars Enhancing Self Driving Prediction with Advanced Deep Learning Techniques

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Abstract-The advancement of driverless cars relies on accurate steering angle prediction to ensure safe and efficient navigation. This work tries to create a deep learning models that minimizes prediction errors while maintaining computational efficiency. The primary objective is to enhance steering control by leveraging advanced neural network architectures. Deep learning models—including EfficientNetV2, EfficientNetV2B3, Xception, and VGG19—were trained on a driving scenario dataset to attain this. Evaluation of the models started with three key performance criteria: loss, mean absolute error (MAE), and mean squared error—MSE. Every model was tuned to maximize generalization and feature extraction therefore guaranteeing strong performance in practical settings. With the lowest error rates (Loss: 0.0110, MAE: 0.0798, MSE: 0.0110), Xception showed great performance among the models tested, therefore demonstrating great accuracy in steering angle predictions. The outcomes underline how much deep learning improves the precision of autonomous car control systems. This work effectively meets its goal by using a very effective model that raises dependability and forecast accuracy. Future research will investigate methods of real-time deployment and further optimization strategies to improve autonomous car decision-making capacity.

Keywords-Driverless Cars, Autonomous Driving, Deep Learning, Steering Angle Prediction and Xception Model.

1. Introduction

Promising improved safety, efficiency, and convenience, self-driving cars are fast changing the scene of modern transportation. Using deep learning, autonomous cars have advanced algorithms that let them negotiate safely without human assistance, make judgments in real-time, and analyze challenging surroundings[1], [2]. A subtype of artificial intelligence (AI), deep learning processes enormous volumes of sensor data—including pictures, lidar, radar, GPS inputs—using neural networks. These networks examine patterns, identify objects, and remarkably accurately predict possible threats by copying human cognitive processes. Self-driving cars greatly increase safety since they help to lower human mistakes that sometimes cause collisions.

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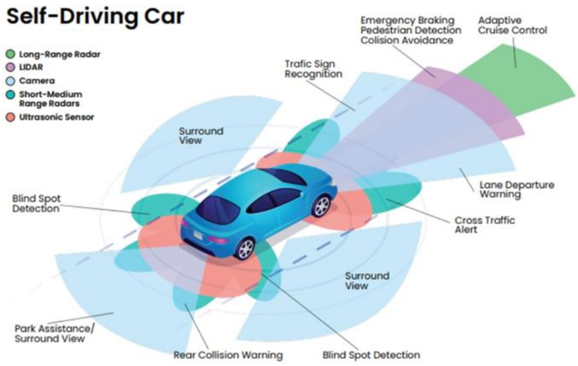

Figure 1 Self-driving cars

The World Health Organization (WHO) estimates that human mistake causes a great share of traffic mishaps. Through constant monitoring, fast reaction times, and the removal of distracted or intoxicated driving, autonomous cars are meant to reduce these dangers. Deep learning models learn constantly from fresh data, gradually improving their performance and hence increasing general road safety. For senior people, those without access to conventional transportation, and those with impairments, self-driving cars provide more mobility[3]–[5]. Emerging as feasible substitutes for traditional transportation choices are autonomous ride-sharing companies and on-demand self-driving taxis. Self-driving vehicles help to improve urban mobility by easing traffic congestion and improving traffic flow, hence lowering greenhouse gas emissions. Autonomous vehicles can detect lanes, people, and other vehicles thanks in great part to Models of deep learning comprising convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Combining data from several sources, sensor fusion methods produce a complete awareness of the surrounding environment[6]–[9]. Furthermore, by modeling several driving situations and learning best answers, reinforcement learning methods help in decision-making. Notwithstanding considerable progress, general adoption of self-driving technology still faces challenges. Important factors influencing the acceptance of autonomous cars are ethical questions, legislation, and public opinion[10]–[12]. Deep learning models' reliability and robustness in dynamic and uncertain environments must be guaranteed by continuous study and improvement. Deep learning self-driving cars are revolutionizing travel by raising mobility, boosting safety, and reducing environmental impact. As long-standing issues are resolved by continuous technological advancements, autonomous automobiles have the power to transform metropolitan settings and rethink the future of transportation. By means of collaboration among researchers, politicians, and corporate leaders, one can realize a safer and more efficient transportation environment[13]–[17].

1.1 Significance and Objectives of the Research Exploration

The changing prospects of deep learning-powered self-driving cars point to the relevance of this work. Autonomous vehicles help to significantly increase road safety by lowering human error, a main cause of traffic accidents. Using state-of- the-art neural network technologies, these cars can grasp sensor data, make real-time decisions, and alter with changing environments. For those with limited access to conventional transportation options, such the

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elderly and those with disabilities, this technological advancement not only provides safety travel but also improves mobility[18]–[20]. Integration of self-driving cars can help to reduce urban congestion, lessen carbon emissions, and maximize traffic flow by means of intelligent routing and vehicle-to--vehicle communication. Notable are also the financial benefits, which could assist to reduce gasoline use, accident costs, and expenses of inadequate transit infrastructure. Research on these innovations will enable technology developers, legislators, and automakers to have perceptive understanding[21]–[23]. The main objectives of this work are to investigate the application of deep learning in enhancing the safety and dependability of self-driving cars, assess their impact on urban mobility and transportation infrastructure, and evaluate their technological difficulties and ethical issues related with their implementation. Moreover, the research aims to provide recommendations for improving autonomous car algorithms and supporting cooperation among technological actors and authorities. By addressing these objectives, the study guarantees responsible use of self-driving cars and ongoing expansion of transportation, therefore supporting the future of vehicles[24]–[26].

1.1.1 Highlighting the Significance of the Research

With self-driving cars, deep learning for enhanced safety and mobility is revolutionizing transportation. By deploying strong neural networks, autonomous automobiles greatly reduce human errors—a major contributing cause to traffic accidents. This system provides safer roads by means of real-time decision-making and adaptive routing. Moreover, self-driving cars improve mobility for those with limited access to traditional transportation as well as for elderly persons and those with impairments[27], [28]. The environmental effect is noteworthy since improved traffic flow and less congestion lower carbon emissions. Economically, good fuel economy and less accidents equate to savings. This study provides insightful information for policymakers and technology developers to direct responsible deployment of autonomous cars[29]. This study supports the creation of creative transportation systems by tackling safety, mobility, and sustainability, so helping to create a safer, more accessible, and efficient future in metropolitan and suburban contexts[30].

By enhancing steering angle prediction using deep learning, this work significantly advances driverless automobile technologies. Safe, quick, dependable autonomous driving depends on accurate steering control. Through bettering neural network architectures, this work lowers prediction mistakes and improves real-time decision-making for self-driving systems. The results help to create intelligent navigation systems, therefore reducing the possibility of mishaps and so enhancing road safety. Moreover, the suggested method helps to lower computing complexity, which increases its practicality for actual implementation. Future developments in intelligent transportation systems and driverless car technologies are grounded in this work.

2. Literature Review

Chen 2021 et al. [31] This study Integrating a particle filter (PF) with deep neural network (DNN) predictions improves visual odometry (VO) robustness. For maximum accuracy, the PF employs motion prediction categorization and uncertainty evaluation. An interval DNN prediction method guarantees real-time performance. Experiments show better tracking accuracy and robustness than current approaches.

Shirley 2021 et al. [32] This study looks at evacuating carless households during hurricanes

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using privately owned autonomous vehicles (AVs). Simulations and survey data show that all houses in need might be evacuated with 30% AV market penetration. AVs could be a consistent addition to conventional evacuation strategies, therefore improving the effectiveness of emergency response.

Lin 2021 et al. [33]This study proposes a framework to analyze and predict mind wandering (MW) in drivers using real-life driving data. By examining personal, contextual, and in-vehicle factors, the study demonstrates that these factors improve MW forecast accuracy. Gradient Boosting Decision Tree algorithms outperform other methods, enhancing traffic safety predictions.

Huang 2021 et al. [34] This work proposes a driving state evaluation method based on overtaking frequency (OTF) for self-driving cars. Combining with the deep deterministic policy gradient (DDPG) approach maximizes safety and efficiency. Simulations in highway settings verify enhanced maneuverability and safety for driverless cars.
Wang 2021 et al. [35] Based on risk homeostasis theory, this work developed a car-following model integrating safety margin (SM) as a risk component. Behavior was much influenced by ADAS and driving experience. Genetic algorithms helped to calibrate the parameters. It displayed less RMSE than the GHR model, therefore improving driving behavior modeling. Next studies will look at driving style.

Table.1 Surveys relevant existing work

Author / Year	Method	Research gap	Controversies	References
Zaghari /2021	Behavioral cloning with LSV-DNN for autonomous driving.	Limited focus on real-world autonomous driving behavior and obstacle detection.	Ethical concerns, safety risks, liability issues, and algorithmic decision-making transparency.	[36]
Zhou/2020	recurrent neural network model.	Not much study on inverse reinforcement learning-based tailored autonomous driving	Debates on autonomous driving safety, ethics, regulation, and human behavior.	[37]
Fang/2020	Regression model	Limited sample size in autonomous driving decision-making using AI.	Ethical dilemmas, safety concerns, liability issues, AI decision-making conflicts.	[38]

Vol. : 20,Issue 2, 2025
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Li/2020	convolutional neural network (CNN)	Lack of industry-specific helmet detection solutions using deep learning.	Privacy concerns, accuracy limitations, and real-time detection reliability debates.	[39]
Chirag Sharma/2020	NVIDIA CNN model.	Lack of real-world testing and generalization in simulations.	Ethical concerns, liability issues, and data privacy in autonomy.	[40]

3. Research Methodology

This work improves driverless automobile steering angle prediction using a deep learning-based method. Driving situations let multiple convolutional neural network (CNN) architectures—including EfficientNetV2, EfficientNetV2B3, Xception, and VGG19—be trained. The premise for model evaluation was key performance indicators including mean absolute error (MAE), loss, and mean squared error—MSE. Hyperparameter change, augmentation, and data preparation helped to increase model performance. To guarantee generalization and dependability, the trained models were put under several scenarios. The last findings underline how well deep learning may improve the stability and accuracy of autonomous car control systems.

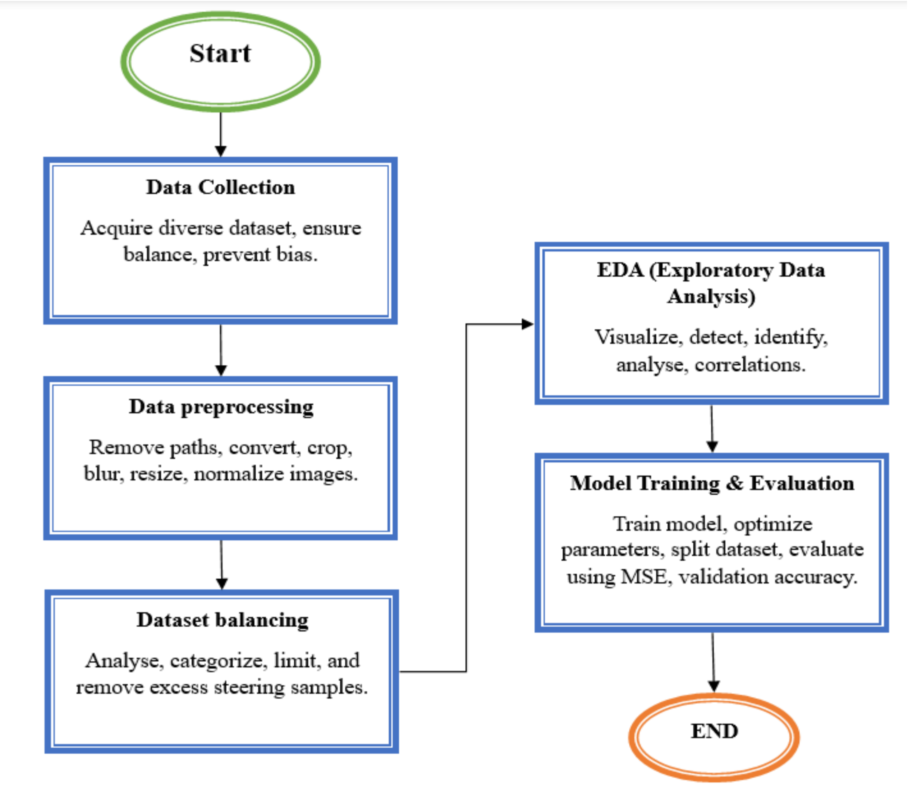

Figure 2 Proposed Flowchart

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3.1 Data Collection

The dataset for training the driverless car model was sourced from [41] provided photos taken from a front-facing camera mounted on a vehicle together with matching steering angle labels for the dataset used to teach the driverless car model. Real-world training is well suited for this dataset since it covers a broad spectrum of driving scenarios including several road environments, lighting variables, weather fluctuations, and road curvatures. Different scenarios enable the model to manage real-world complexity including quick curves, sudden barriers, and different road textures, therefore facilitating improved generalization. Every picture frame presents an accurate portrayal of actual driving conditions, which lets the model convert visual input to exact steering decisions. Moreover included in the dataset are required metadata, which is absolutely essential for data organization and structure before preparation. Avoiding bias towards straight-path driving required a balanced dataset achieved by way of examination of the distribution of steering angles. Any imbalance in turns instead of straight motions could lead to poor model performance in conditions requiring frequent steering corrections. As such, the dataset was examined to verify that it contained sufficient variation of turning angles, which is required for learning robust steering behaviors. Different driving behaviors help the program to generate reliable projections under many road conditions. Since it guarantees that it learns from a realistic and well-organized collection of driving circumstances to improve its decision-making capacity, this dataset offers the foundation for developing a deep learning-based steering control model.

3.3 Data Preprocessing and Balancing

Ensuring high-quality data for training the self-driving car model depends on the preprocessing stage, so it was absolutely important. Raw steering angle values in the dataset demanded improvement prior to model development. First, the removePath() tool eliminated extraneous file paths such that just pertinent data remained for additional use. The imbalance in steering angle distribution in autonomous driving datasets is one of the main difficulties since most of the data relates to straight-road scenarios and can cause possible bias in model predictions. Steering angles were divided into 25 bins to help to solve this problem by allowing a disciplined arrangement of several turning angles. Any extra data over a maximum threshold of 500 samples per bin was eliminated, therefore guaranteeing that the dataset kept an even distribution of turns and straight lines. This stage is crucial to prevent the model from overfitting to straight-driving situations and increase its capacity to generalize over many road conditions.

By means of a histogram analysis of steering angles—which visually distinguished overrepresented and underrepresented groups—dataset balancing was significantly improved. Originally dominating the dataset, straight-driving situations could lead to underperformance of the model during turns. The model was trained on a wide spectrum of driving conditions by excluding too straight-driving samples and preserving a balanced representation of several steering angles, hence increasing its adaptability to real-world surroundings. The balancing approach guarantees that the model responds dynamically to changing driving conditions and does not get biassed toward straight routes.

The image routes and matching steering values were arranged into pairs and kept as NumPy arrays for effective data handling to ready the final dataset. Training and validation sets were then created from these ordered data pairings, therefore enabling the model to learn from a balanced dataset while under evaluation on unaccustomed data. These preprocessing and balancing methods have their rationale in their capacity to raise model resilience. Binning steering angles guarantees organized learning; threshold-based sample filtering inhibits overfitting to dominant driving habits. This method improves the capacity of the model to produce correct steering predictions under different circumstances, therefore enabling more consistent and flexible autonomous driving performance.

Preprocessing & Balancing Pseudocode

```
# Function to Remove Unnecessary File Paths
Function removePath(file_path):
   Extract filename from file_path
   Return filename
End Function

# Apply Path Cleaning to Dataset Columns
For each column in ['center', 'left', 'right'] of dataset:
   Apply removePath function to remove unnecessary file paths
End For

# Function to Load Image Paths and Steering Values
Function loadImageSteering(datadirectory, dataset):
   Initialize imagePath list
   Initialize steeringPath list
   For each row in dataset:
      Append image path to imagePath list
      Append corresponding steering value to steeringPath list
   End For
   Return imagePath, steeringPath
End Function

# Function for Image Preprocessing
Function imagePreprocessing(img_path):
   Load image from img_path
   If image is grayscale:
      Convert to RGB
   End If
   Crop the region of interest
   Convert image to YUV color space
   Apply Gaussian blur for noise reduction
   Resize image to (200, 66)
   Normalize pixel values to range [0, 1]
   Return preprocessed image
End Function

# Apply Image Preprocessing to Training Data
For each img in x_train:
   Apply imagePreprocessing function
End For

# Dataset Balancing
Create histogram of steering angles
Determine bin distribution (25 bins)
For each bin:
   If bin contains more than 500 samples:
      Randomly remove excess samples to limit bin to 500 samples
   End If
End For

# Ensure Balanced Dataset
Store preprocessed and balanced image-steering pairs
Convert to NumPy arrays for training and validation splits
```

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3.3 Exploratory Data Analysis (EDA)

The distribution of the dataset and possible biases were investigated by means of exploratory data analysis (EDA). Strong imbalance in the steering angle distribution was found by a histogram analysis; straight-line steering values had much more frequency than turns. This implies that the dataset's vehicles mostly moved straight, hence possible model bias results. Steering angles were divided into 25 bins, with each bin capped at a maximum of 500 samples to guarantee a more consistent representation and help to offset this. A density chart verified even more the predominance of nearly zero steering angles. Numerical aspects were also examined using boxplots, which highlighted speed and steering value outliers that were then handled accordingly. A correlation heat map revealed minor correlations between steering, throttle, and speed, therefore indicating little redundancy among the variables. Important for model generalization, environmental factors including changes in lighting, occlusions, and road textures were evaluated using image visualizations. Moreover, brightness levels were investigated to see how they affected steering behavior, therefore enabling the identification of any deviations. Extreme steering values resulting from mislabeling were found and addressed as outliers meant to stop distorted learning. These EDA discoveries directed preprocessing techniques to guarantee data balance and enhanced training effectiveness. Understanding dataset features, biases, and feature connections helped the preprocessing procedure to be tuned to increase model robustness, thereby boosting the steering prediction accuracy for real-world driving conditions.

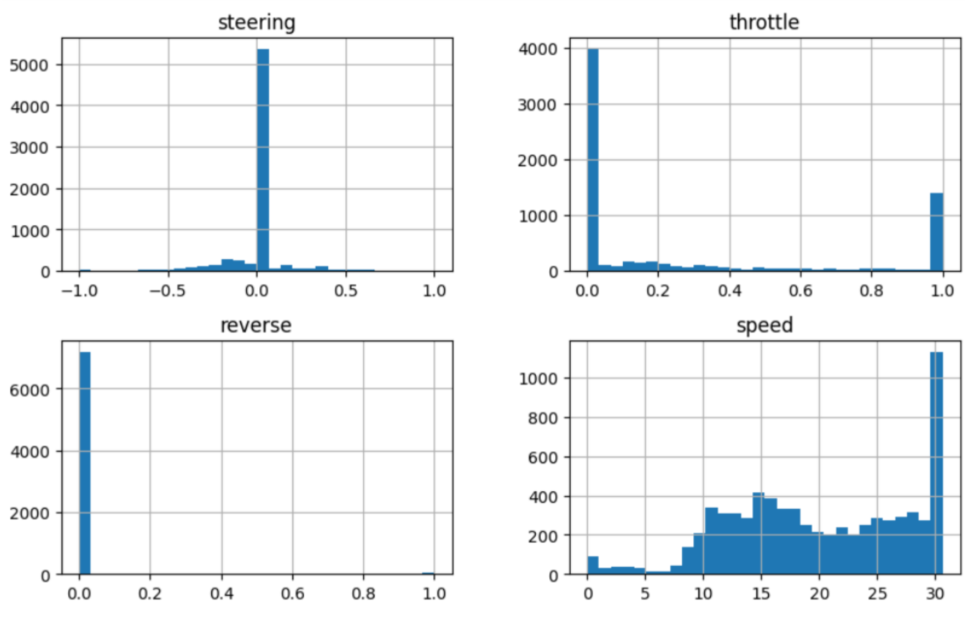

Figure 3 Histogram analysis of steering, throttle, reverse, and speed distributions.

The histograms visualize the distribution of steering, throttle, reverse, and speed values in the dataset. Steering and reverse exhibit strong imbalance, with most values concentrated around zero. Throttle and speed show varied distributions, highlighting potential biases that require balancing before training.

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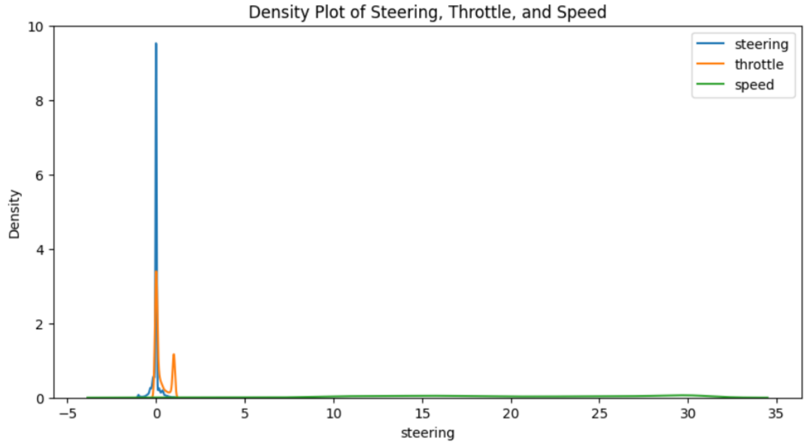

Figure 4 Density plot of steering, throttle, and speed distributions.

This density plot illustrates the distribution of steering, throttle, and speed values. Steering and throttle exhibit sharp peaks near zero, indicating significant imbalance, while speed is more evenly spread. The visualization highlights the need for dataset balancing to ensure effective model training.

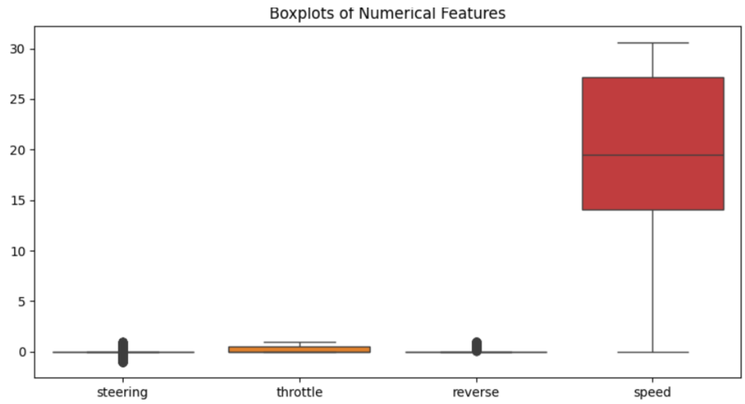

Figure 5 Boxplots of numerical features: steering, throttle, reverse, and speed.

This boxplot visualizes the distribution of key driving parameters. Steering, throttle, and reverse exhibit minimal variance with outliers, while speed shows a wider range and variability. The presence of outliers suggests potential data imbalance, which may require preprocessing for effective model performance.

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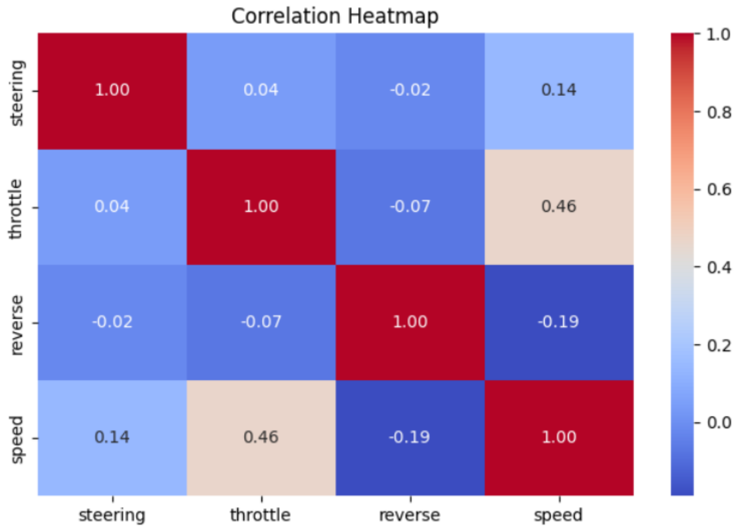

Figure 6 Correlation heatmap of steering, throttle, reverse, and speed parameters

This heatmap visualizes the correlation between key driving features. Steering has minimal correlation with other variables, while throttle shows a moderate positive correlation (0.46) with speed. Reverse has a weak negative correlation with speed (-0.19). These insights help in understanding relationships between driving inputs and vehicle dynamics.

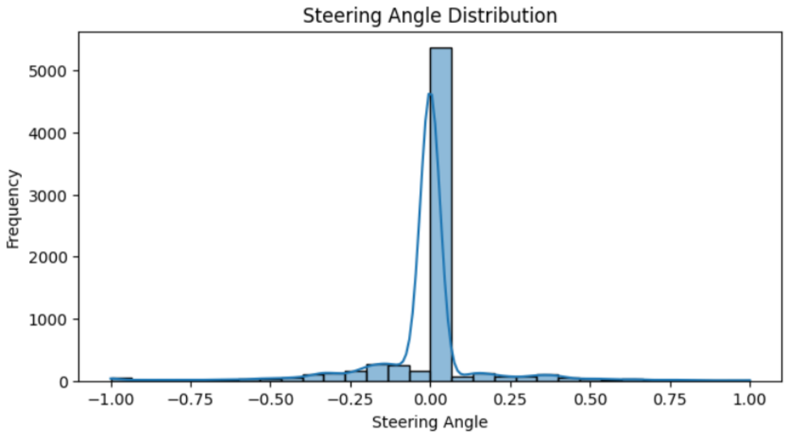

Figure 7 Steering Angle Distribution Histogram

This histogram represents the distribution of steering angle values in a dataset. The plot shows that most steering angles are concentrated around 0, indicating that the vehicle primarily moves in a straight direction. The distribution has a sharp peak at zero with relatively few extreme left or right turns, suggesting cautious or stable driving behavior.

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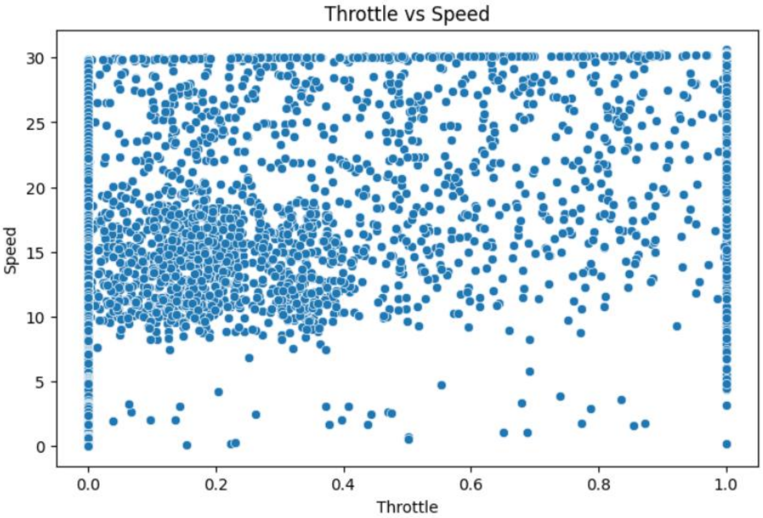

Figure 8 Scatter Plot of Throttle vs Speed

This scatter plot illustrates the relationship between throttle input and vehicle speed. The data points show that a large concentration of values is observed at lower throttle values (between 0.0 and 0.3), indicating frequent operation in this range. The speed values are widely distributed, suggesting that speed is influenced by factors beyond just throttle, such as road conditions or external forces. The presence of points at throttle values of 0 and 1 may indicate instances of idling or full acceleration.

3.4 Proposed Model Architecture

- **Proposed Model Architecture for Steering Angle Prediction**

Applying a feature extraction backbone, Squeeze-and- Excitation (SE) blocks, and an attention mechanism to enhance steering angle prediction in self-driving automobiles, the proposed model integrates deep learning approaches. Through a strong regression framework, the architecture is tuned to collect hierarchical spatial information, improve useful signals, and hone predictions.

- **Feature Extraction Using Pretrained Models**

Pretrained architectures—including EfficientNetV2, EfficientNetV2B3, Xception, and VGG19—all trained on ImageNet form the foundation of the model. These models effectively extract from input photos low-level to high-level spatial and contextual elements.

  - Depthwise-separable convolutional layers ensure computational efficiency while preserving essential spatial information.
  - **Global Average Pooling (GAP)** is used to reduce dimensionality while retaining feature integrity.
  - Batch normalization is applied to stabilize learning and improve convergence speed.

- **Feature Enhancement Using Squeeze-and-Excitation (SE) Blocks**

By using a channel-wise attention method, SE blocks are included to improve the obtained features by stressing significant information and so reducing redundant signals. The SE block acts in the following ways:

- **Global Average Pooling (GAP):** Computes feature importance across all channels.
- **Fully Connected Layers:**
- First layer deals with ReLU activation adds non-linearity.
- Second layer functions Sigmoid activation to produce weight for attention.
- **Feature Recalibration:** The recalibrated features are multiplied element-wise with the original feature maps, amplifying crucial information.

- **Attention Mechanism for Enhanced Feature Representation**

Long-range dependencies captured by an attention method help to enhance feature learning even more. This approach generates attention scores by means of a query-key attention operation, therefore optimizing feature interactions:

- Utilizing trainable weight matrices, compute Query (Q) and Key (K) transformations.
- Calculate attention scores by first softmax normalizing after dot product of Q and K.
- Create weighted feature representations by means of value (V) attention scores applied with regard to relevance.
- Change the feature space such that the model becomes more sensitive to important steering cues.

- **Regression Output for Steering Angle Prediction**

The last feature representation passes through a completely connected layer producing the expected steering angle:

- One neuron with a linear activation function makes up the output layer, therefore guaranteeing continuous value prediction.
- To stop overfitting, a 0.5 dropout layer is used.

- **Model Training and Evaluation**

Twenty percent of the dataset is used for testing and eighty percent for training. Images go through preprocessing covering cropping, YUV color space conversion, Gaussian blur application, and normalizing. The training stream comprises of:

- **Optimizer:** Adam (adaptive learning rate).
- **Loss Function:** Mean Squared Error (MSE).
- **Metrics:** Mean Absolute Error (MAE) and MSE.
- **Batch Size:** 32.
- **Epochs:** 50, with a learning rate scheduler decreasing at 10 and 20 epochs to enhance convergence.

This ordered framework efficiently collects, enriches, and refines deep visual information, hence enhancing the accuracy of steering angle forecasts and advancing self-driving perception models.

Vol. : 20,Issue 2, 2025
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Table 2 Hyperparameter Details

Hyperparameter	**Value**
Models	EfficientNetV2, EfficientNetV2B3, Xception, VGG19
Input Shape	(66, 200, 3)
Base Model	EfficientNetV2 / EfficientNetV2B3 / Xception / VGG19 (Pretrained on ImageNet)
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Batch Size	32
Activation Function	ReLU (except output layer: Linear)
Dropout Rate	0.5 (in fully connected layers)
Pooling Type	GlobalAveragePooling2D
Batch Normalization	Applied after feature extraction and dense layers
Attention Mechanism	Custom AttentionLayer for query-key attention
Squeeze-and-Excitation Block	Applied after feature extraction to enhance channel-wise features
Feature Extraction	EfficientNetV2 / EfficientNetV2B3 / Xception / VGG19
Metrics Used	MSE, MAE
Number of Epochs	50 (Adaptive learning rate with decay at 10 and 20 epochs)
Learning Rate Schedule	Initial: 1e-3, reduced by 0.1 at 10 epochs, 0.01 at 20 epochs

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1) Adam Optimization

Adam is a strategy whose general usefulness combines elements of momentum and RMSprop optimization techniques. The following computation provides the update rule for the angles θ in the Adam optimization technique:

$$\theta_{t+1} = \theta_t \frac{\alpha \cdot m_t}{\sqrt{v_t} + \epsilon} \tag{1}$$

Theta is the model's parameter symbol; alpha is the learning rate; m t is the exponentially declining average of previous gradients; v t is the exponentially declining average for past squared gradients; epsilon has the small constant guaranteeing division by zero using the Adam optimization update method.

2) ReLU

Often seen in neural networks, the rectified linear unit—also called ReLU—is an activation function. Should the input be positive, it returns the current value straight forward; ought to it be negative, it returns zero. ReLU not only encourages sparsity in activations but also aids to tackle the vanishing gradient problem during learning. Deep learning systems find this common choice since it is both straightforward and efficient.

$$f(x) = \max(0, x) \tag{2}$$

Here x is the function's input; f(x) is its output. The ReLU function either returns zero or positive (x) inputs directly straight-forwardly. Since they promote sparsity and reduces the impact of the vanishing gradient problem, neural networks largely rely on this fundamental piecewise-linear function for training.

3) Softmax

Because it helps to standardize the scores dependent on input, softmax is a basic element of neural networks. For every input value, its computation is divide the exponential by the total of all the exponentials. This normalizing method guarantees that the output values lie between zero and one, therefore enabling one to correctly represent probability. Softmax helps to simplify tasks involving categorization as the output of the network can now be understood as the probability of each class. In machine learning, task depend on neural network predictions; so, softmax is a required tool to convert those predictions into useful probability.

$$Softmax(x_i) = \frac{e^{xi}}{\sum j^{e^{xj}}} \tag{3}$$

4. Result & Discussion

Using Loss, Mean Absolute Error (MAE), as well as Mean Squared Error (MSE) as main criteria, the performance of several models for steering angle prediction within the driverless car system was assessed. The outcome are compiled in the table below:

- **Loss Function**: Calculates the discrepancy in model forecasts, therefore guiding the optimization of learning.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{Y}i.\log(\mathcal{Y}i) \tag{4}$$

- **Mean Absolute Error (MAE):** Calculates, from expected to actual values, an average absolute difference using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - x| \tag{5}$$

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- **Mean Squared Error (MSE):** Squares variations between expected and actual values, so lowering significant mistakes, given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{6}$$

Table 3 Performance Evaluation of Proposed Models

Model	Loss	MAE	MSE
EfficientNetV2	0.0726	0.2004	0.0726
EfficientNetV2B3	0.0654	0.1875	0.0654
Xception	0.0110	0.0798	0.0110
VGG19	0.0563	0.1757	0.0563

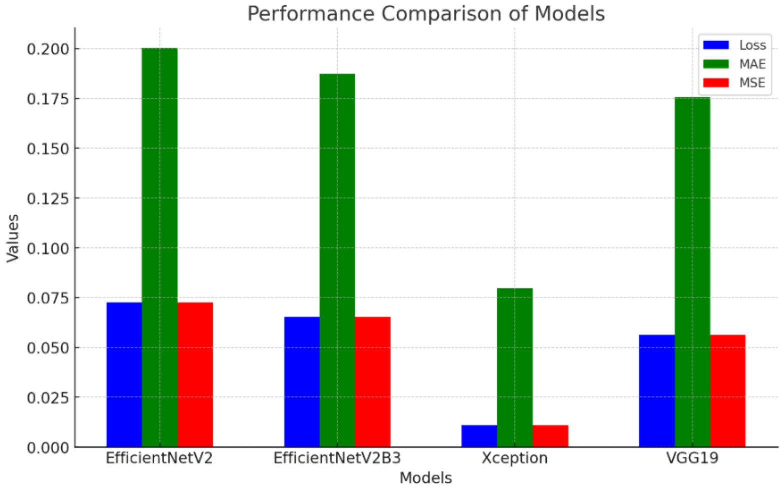

Figure 9 Performance Graph of Proposed Models

Table Performance Evaluation of Proposed Models shows the Xception model to show the best general performance. Its much lower scores in all three performance measures—loss (0.0110), mean absolute error (MAE), and mean squared error—MSE—draw this conclusion. Xception is the most dependable methodology for guiding angle estimate in autonomous automobiles since lower values for these measures point to more accurate forecasts.With EfficientNetV2B3 performing better than EfficientNetV2 in all three measures, both EfficientNetV2 and its variation EfficientNetV2B3 exhibit competitive performance. Higher MAE and MSE values in both models, however, indicate that their forecasts differ more from real values than in Xception. VGG19 falls short of Xception's accuracy even though it beats EfficientNetV2 and EfficientNetV2B3.Xception's depthwise separable convolutions, low computational complexity, and strong feature extraction power help to explain its outstanding performance. These benefits help it to more successfully learn complex patterns in steering angle predictions than in other models. Xception is thus the most appropriate model for practical implementation since it provides better precision, lower mistake rates, and greatest performance in autonomous driving uses.

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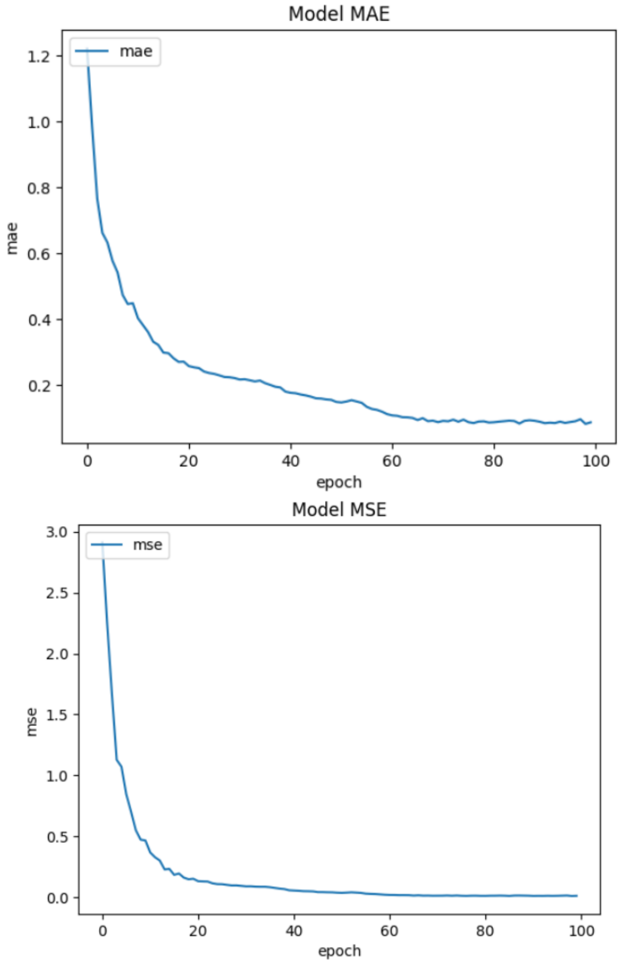

Figure 10 MAE MSE graph of Xception model

The Mean Absolute Error (MAE) and Mean Squared Error (MSE) of the Xception model across 100 epochs are shown graphically. Both measures reveal a notable drop, which stabilizes about 60 epochs and points to good learning. The declining trend points to better steering angle prediction, therefore verifying the accuracy and resilience of the model in applications for driverless cars.

Table 4 Comparative Analysis Between Existing Work with Proposed Best model

Model	Loss	MAE	MSE	Ref.
NVIDIA PilotNet	0.0205	0.0902	0.0205	[42]
ResNet-50	0.0153	0.0850	0.0153	[43]
InceptionV3	0.0187	0.0885	0.0187	[44]
Xception	**0.0110**	**0.0798**	**0.0110**	--

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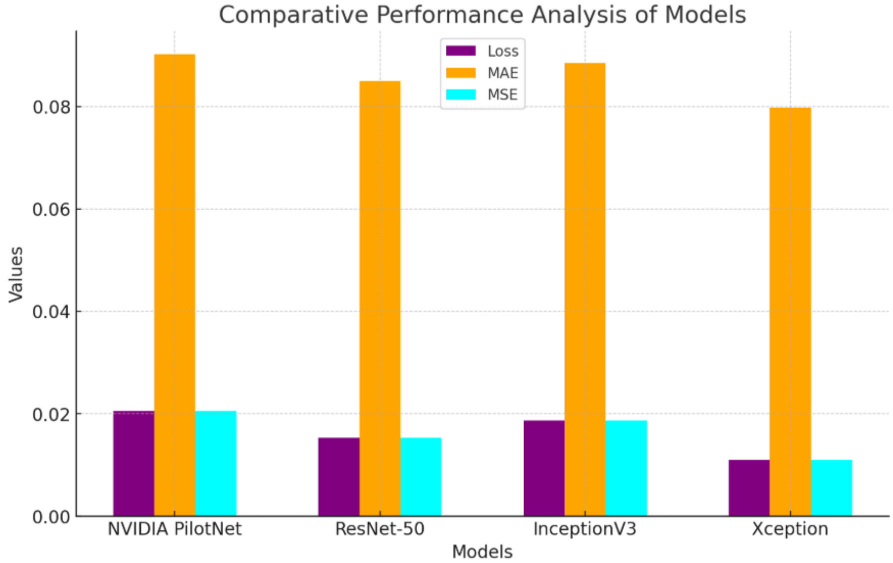

Among the models, Xception shows the lowest Loss, MAE, and MSE values, therefore demonstrating exceptional performance in tasks involving steering angle prediction. Higher mistake metrics in NVIDIA PilotNet, a trailblazing end-to--end learning model for self-driving cars, point to room for development over Xception.Though they still lack Xception's accuracy, ResNet-50 and InceptionV3 models—known for their deep architectures and feature extraction powers—do better than PilotNet.Based on its reduced error measurements, the suggested Xception model beats current models in the field of autonomous driving. It is a strong choice for guiding angle prediction activities since its architecture efficiently catches complicated patterns in driving data.

5. Conclusion

This work sought to maximize steering angle prediction to build an effective deep learning model for autonomous driving. Improving prediction accuracy while lowering mistakes was the main goal in order to guarantee real-time applicability in autonomous systems. Many deep learning models— Train and evaluate EfficientNetV2, EfficientNetV2B3, Xception, as well as VGG19 based on Loss, Mean Absolute Error (MAE), as well as Mean Squared Error (MSE). Among them, Xception showed the lowest error metrics (Loss: 0.0110, MAE: 0.0798, MSE: 0.0110), hence far beating the other models.Xception's superiority was further confirmed by a comparison study including current state-of- the-art models (NVIDIA PilotNet, ResNet-50, and InceptionV3). Using depthwise separable convolutions helped it to perform the best by lowering computational complexity while maintaining great accuracy. This work effectively meets its aim by suggesting a model that greatly increases steering angle prediction, hence improving the dependability of autonomous driving systems. The results verify that Xception is the best option for practical implementation since it strikes a compromise between efficiency, accuracy, and computational feasibility. To maximize decision-making in autonomous navigation even more, future studies could investigate hybrid models and reinforcement learning approaches.

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