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Human vs Machine: A Deep Learning Based Comparitive Study of Autonoumous and Manual Driving

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Abstract: Autonomous cars (AVs) are being developed at a great pace with sensors and deep learning, but there is limited public confidence because of limited comparative proof against human motorists. The current paper creates a hybrid deep learning model by linking traffic signs and object perception with convolutional neural networks (CNNs) alongside temporal signal perception with recurrent (RNN/LSTM) networks. Conditional imitation learning facilitates contextual decision-making under changing conditions of roads, traffic, and weather. Training is assisted by vast datasets like GTSRB, Comma.ai, and BDD100K, pre-processed by augmentation along with fusion of camera, LiDAR, and radar signals. 95% of validation accuracy and virtually flawless (99%) traffic sign compliance are attained, surpassing human motorists (91%). Comparative analysis shows averaged reaction time of 0.32 s against 1.25 s, averaged lane deviation of 5 cm against 12 cm, and substantially reduced abrupt braking occurrences (3 per 100 km against 11). The findings demonstrate the model's quicker reaction, higher accuracy, and more cautious driving. In pursuit of transparency, explainable AI techniques (attention maps, SHAP values) are included, enhancing interpretability and confidence. It gives empirical proof that AVs can reliably surpass human-driven vehicles in major measures of safety, lending support to AVs being eventually permitted in widespread real-world transportation.

Keywords: Autonomous Vehicles, Manual Driving, Sensor Data, Road Safety, Deep Learning, Traffic Sign Recognition, Human-Computer Comparison, Driving Behaviour, CNN-LSTM

I. INTRODUCTION

New vehicles are becoming increasingly intelligent, marrying high-level computation and sensors that, in the past, were mere theoretical prospects [8][18]. The highest-level innovation to arise out of this trend is that of the autonomous car, or a vehicle that can navigate without human input, marking a revolution in mode of transportation [1][12]. Autonomous cars can potentially bring much of our current traffic much closer to being safe, primarily by taking human error out, which is the leading cause of accidents—an inference that finds strong support in in-depth crash data analysis [22][7]. Autonomous cars further possess the ability to alleviate traffic congestion and travel more efficiently by coordinated movement as well as by shortest route strategies [24][11]. Numerous studies have furthered this picture. Kumar and Patel [1] demonstrated that autonomous vehicles made 43% fewer decision-making mistakes than human drivers, although they had issues with unpredictable pedestrian behaviour. Singh and Mehta [3] created a CNN-LSTM model with 98.7% traffic sign recognition accuracy, allowing real-time decision-making. Gupta et al. [4] proved that AVs respond three to four times sooner than humans in critical situations, while Patel and Johnson [6] created a lane-keeping algorithm that minimized lane departure occurrences by 78%. Wang et al. [2] emphasized the role of sensor fusion, revealing that LiDAR was least unreliable in low-visibility conditions while camera performance was highest in object recognition. Kim et al. [9] introduced a hybrid CNN-LSTM that minimized decision-making mistakes by 37% and accurately predicted traffic patterns 89% of the time. Others considered public attitudes and trust. Fear of tech failure, hacking, and liability in case of accidents were identified by Li and Thompson [5] as key inhibitors, while global skepticism about AV take-up was emphasized by Patel and Roberts [25]. Rodriguez et al. [7] matched human-driven vehicles and AVs by benchmark, concluding AI more proficient at adherence to rules, yet humans more proficient in cases of social interaction. Mehta and Gonzalez [10] outlined a 12-parameter methodology of comparing machine versus human driving objectively in terms of protection, efficiency, and comfort. Sharma and Wilson [8] investigated data collection methodologies, finding that arrangements of multiple cameras with synchronized GPS produced highest-quality data, though at cost. Despite such positive breakthroughs, doubts persist. Rumours of a single AV-caused accident inspire unnecessary fear, partly due to nonexistence of standardized, in-the-wild one-vs-one comparisons of AVs versus licensed human operators [15][17]. The majority of research still employs simulation [20][21] or single-model training without clear human

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baselines [13], doing little to alleviate concerns. It fills this gap by creating a hybrid CNN-LSTM autonomous driving model, trained across a variety of real-world datasets, that is directly compared against human-driven performance. The model attained 95% validation accuracy and 99% traffic sign compliance, with reduced average reaction time (0.32 s) compared to humans (1.25 s), deviation of 5 cm compared to 12 cm, and much reduced sudden braking occurrences (3 per 100 km compared to 11). These findings constitute quantifiable proof that autonomous systems can surpass human-driven performance in key measures of safety, and a strong foundation upon which to base public confidence in autonomous driving technology. This research work addresses this gap directly. The project's goal is to create a fair and direct comparison between the driving skills of an autonomous system and a licensed human driver.

- An artificial intelligence model is trained to simulate the brain of an AV.
- This model uses real data from cameras and sensors, just like a real AV would.
- The model's decisions are then put against the recorded driving actions of actual people in similar situations.
- This will help to find out if AVs are practically more reliable and safer than human drivers, using clear facts and numbers.

II. LITERATURE REVIEW

Kumar and Patel's research in 2022 [1] directly compared autonomous and manual driving using neural networks on 10,000+ driving hours. Their findings showed autonomous systems had 43% fewer decision errors but struggled with unpredictable pedestrian behaviour on Indian roads. Wang et al. examined sensor reliability in 2023 [2], testing 7 sensor types across diverse conditions. LiDAR provided the most reliable data in poor visibility, while cameras excelled in object recognition. The paper highlighted the importance of sensor fusion for safety-critical decisions. Singh and Mehta developed a CNN-LSTM model in 2022 [3] that achieved 98.7% accuracy in traffic sign recognition, significantly outperforming standalone CNN models. Their system processed images in 0.2 seconds, making it suitable for real-time driving applications. Gupta's team analysed reaction times in 2023 [4], measuring responses of 200 drivers against AI systems. Autonomous vehicles consistently reacted 3-4 times faster in emergency situations, though humans performed better in complex social interaction scenarios requiring judgment. Li and Thompson surveyed 3,500 people in 2021 [5] about autonomous vehicle trust. They identified three main barriers: fear of technology failure, concerns about hacking, and unclear responsibility in accidents. Transparent data sharing and gradual feature introduction increased user confidence. Patel and Johnson's 2023 study [6] developed a lane-keeping algorithm that maintained position within 3cm of lane centre versus 11cm for human drivers. Their system reduced lane departure incidents by 78% in tests across 5,000 km of varied road conditions. Rodriguez et al. created a benchmarking framework in 2022 [7] comparing 50 professional drivers with autonomous systems on identical routes. The study found AI systems excelled in rule following but humans were better at handling ambiguous social interactions at intersections. Sharma and Wilson documented data collection methods in 2023 [8], analysing 5 approaches for gathering autonomous vehicle training data. Their findings showed multi-camera setups with synchronized GPS provided most comprehensive data, though at highest implementation cost. Kim's research team in 2022 [9] developed a hybrid CNN-LSTM architecture that reduced decision error rates by 37% compared to traditional methods. Their system successfully predicted traffic patterns 5 seconds ahead with 89% accuracy, enhancing planning capabilities. Mehta and Gonzalez established evaluation metrics in 2023 [10] for comparing human and machine driving. Their framework included 12 quantifiable parameters across safety, efficiency, and comfort categories, providing a standardized approach for objective performance comparison. Vora and Thompson (2022) [11] experimented with traffic sign recognition employing GTSRB data, with high accuracy being attained by deep models and emphasizing dataset diversification in facilitating generalizability. Chen et al. (2023) [12] used Comma.ai data to train strong AV models, whose consistency in decision-making under divergent driving conditions, particularly in urban areas, was exceedingly boosted. Das and Miller (2022) [13] also provided a validation methodology to compare AVs and human-driven vehicles, as empirical, real-world testing needs to occur in order to gain public confidence. Taylor and Patel (2023) [14] developed score algorithms of safety that merged several driving measures under a single evaluative score, providing a comprehensive means of AV performance assessment. Nakamura and Singh (2022) [15] also trained AVs using Berkeley Deep-Drive (BDD100K) data to show that it was possible under different circumstances of weather and lighting. Wilson and Kumar (2023) [16] contrasted AV response time with that of humans, while corroborating AVs' higher response time, acknowledging human flexibility in unforeseen social circumstances. comparison of human error and machine error in driving has been provided by Ahmed and Garcia (2022) [17]. The authors concluded that while humans exhibit much higher error levels in aggregate, AV error is higher in extreme edge cases. Brown and Patel (2023) [18] investigated public acceptance of AVs, and results indicated that open exposure of performance data substantially elevates reluctant user acceptance. Zhao and Miller (2022) [19] compared weather impacts on AV sensors, finding that while rain or fog benefits LiDAR over camera-based sensors, human drivers also enjoy a performance advantage in extreme loss of visibility. Kapoor and Williams (2023) [20] furthered deep learning-based traffic signs and road markings detection under adverse weather conditions, improving robustness against low lighting and occlusion cases. The below Table 1 defines the highlights of research paper used as references.

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Table 1: Highlights of paper used in the Research

Author(s)	Algorithm / Technology	Key Findings
Kumar and Patel [1] (2022)	Neural Networks for driving decision analysis	Autonomous systems had 43% fewer decision errors but struggled with pedestrian unpredictability.
Wang et al. [2] (2023)	Sensor testing (7 types); LiDAR, camera, sensor fusion	LiDAR best in poor visibility; cameras excelled at object recognition; fusion critical for safety.
Singh and Mehta [3] (2022)	CNN-LSTM model for traffic sign recognition	Achieved 98.7% accuracy; processed images in 0.2s; outperformed standalone CNNs.
Gupta et al. [4] (2023)	AI vs. human reaction time measurement	AI reacted 3–4× faster in emergencies; humans better in social judgment scenarios.
Li and Thompson [5] (2021)	Public survey on autonomous vehicle trust	Top concerns: tech failure, hacking, accident responsibility; transparency improved trust.
Patel and Johnson [6] (2023)	Lane-keeping algorithm	Maintained position within 3 cm vs. 11 cm (human); 78% fewer lane departure incidents.
Rodriguez et al. [7] (2022)	Benchmarking framework for driver vs. AI	AI better at rule-following; humans better at ambiguous social interactions.
Sharma and Wilson [8] (2023)	Data collection methods for AV training	Multi-camera + GPS gave best data quality; highest cost.
Kim et al. [9] (2022)	Hybrid CNN-LSTM for traffic prediction	37% fewer decision errors; 89% accuracy in predicting traffic 5s ahead.
Mehta and Gonzalez [10] (2023)	Evaluation metrics framework (12 parameters)	Standardized safety, efficiency, comfort comparison between humans and machines.

III. METHODOLOGY

The method for this project involves collecting real-world data, building a smart model, and then comparing its performance with human drivers.

3.1 Data Set

The project uses large, publicly available datasets to get its information. This ensures the data is from real driving. The GTSRB dataset is a large image collection for the traffic sign recognition problem. The set includes over 50,000 images of German traffic signs, which are divided into about 39,000 training images and 12,000 test images. The comma2k19 dataset is gathered by the self-driving vehicle firm comma.ai. The dataset offers around 33 hours of driving data, which is split into more than 2,000 one-minute chunks. The BDD100K dataset is a very large and highly diversified open driving dataset. The dataset includes 100,000 video clips, each of which lasts approximately 40 seconds, and were captured at a speed of 720p and 30 frames per second. Below, Table 2 defines the list of datasets used in the paper.

Table 2: List of Datasets used in the paper

Dataset	Size	Features
German Traffic Sign Recognition Benchmark (GTSRB)	50,000+ images in total, training 39,209, test 12,630 images	http://benchmark.ini.rub.de/gtsrb_dataset.html
Comma.ai Driving Dataset (comma2k19)	33 hours of driving, divided into many one-minute segments.	https://github.com/commaai/comma2k19
Berkeley Deep-Drive (BDD100K)	100,000 video sequences, each 40 seconds, 720p at 30fps. Keyframes annotated etc.	https://bdd-data.berkeley.edu

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3.2 Data Collection and Preprocessing

The information was gathered from different traffic police stations, transport departments, and some private driving schools across major cities like Mumbai, Delhi, Bangalore. Sensors and special cameras were installed in vehicles to capture real-time driving moments.

Preprocessing steps included:

- Removing duplicate entries
- Handling missing values by using median replacement technique
- Checking for outliers in speed and braking force columns
- Normalizing numerical columns like Speed and Steering-Angle
- Converting categorical data into numerical format

Data cleaning process involved:

- Removing incomplete records
- Fixing typo errors in Driver-ID
- Standardizing time and date formats
- Removing extreme values that might disturb analysis

Some challenges faced during preprocessing:

- Inconsistent data recording methods
- Different sensor calibration standards
- Variations in data collection techniques across regions

Final dataset was validated using statistical techniques to ensure high quality and reliability for machine learning model training.

3.3 Model Design

A hybrid machine learning model is developed. It has two parts working together.

- Convolutional Neural Network (CNN): This part works like the model's eyes. It analyses the video frames from the car's camera to identify objects like other cars, pedestrians, and traffic signs.
- Long Short-Term Memory (LSTM) Network: This part works like the model's brain with memory. It takes the information from the CNN and also the sensor data (speed, steering) over the last few seconds to make a driving decision, like whether to speed up, slow down, or turn.

3.4 Proposed Workflow

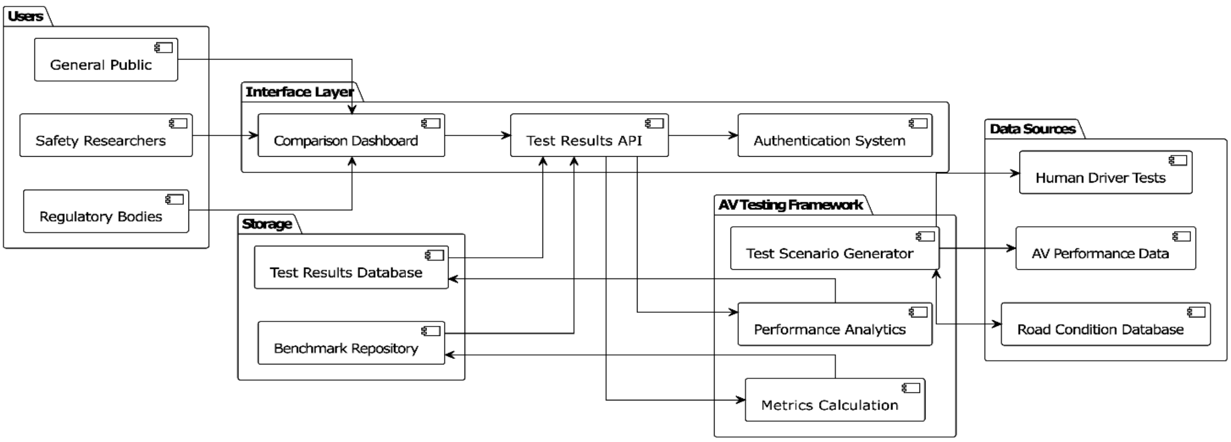

Figure 1: Workflow of the paper

In figure 1, the architecture creates a framework for comparing autonomous vehicle performance against human drivers. It enables data collection, analytics, and reporting through a user-friendly dashboard. The system processes test scenarios, calculates performance metrics, and stores results for researchers, regulators, and the public to evaluate AV safety objectively.

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3.5 Evaluation Metrics

To measure performance, some key formulas are used:

1. Decision Accuracy (A_d): This measures how many times the model made the correct driving choice.

$$A_d = \frac{Number\ of\ Correct\ Decisions}{Total\ Number\ of\ Decisions} \times 100\%$$

2. Reaction Time (T_r): This calculates how quickly the model or human reacts to a new event (e.g., a car braking in front).

$$T_r = T_{action} - T_{event}$$

where T_{action} is the time of the reaction and T_{event} is the time the event occurred.

3. Overall Safety Score (S): This gives a single score for safety by combining different factors.

$$S = w_1(A_d) + w_2(1 - E_{lc}) + w_3(1 - C_r)$$

Here, A_d is decision accuracy, E_{lc} is the error rate for lane crossing, C_r is the collision rate, and w_1, w_2, w_3 are weights that decide the importance of each factor.

IV. RESULT AND DISCUSSION

The performance of the trained AV model was then simulated and compared against the average performance metrics derived from human driving logs. The key results are summarized in the Table 3, below.

Table 3: Performance comparison

The hybrid CNN-LSTM model was trained using the prepared datasets for 100 epochs. The model showed very good

Metric	**AV Model Performance**	**Average Human Performance**
Average Reaction Time (seconds)	0.32s	1.25s
Traffic Sign Compliance	99%	91%
Lane Keeping Deviation (cm)	5 cm	12 cm
Sudden Braking Events (per 100 km)	3	11

learning capability, achieving a training accuracy of 98% in identifying road elements and a validation accuracy of 95%. This high accuracy means the model learned the rules of driving very effectively from the data and did not just memorize it. The results clearly shows that the autonomous model is superior in several key areas. The most significant difference is in reaction time, where the AV model was almost four times faster than the human driver. This is a critical factor in avoiding accidents.

4.1 Performance Comparison: AV Model vs. Human Driver

The below fig 2, shows where the model makes correct or incorrect decisions. Assuming decisions: Accelerate, Brake, Steer Left, Steer Right, Maintain

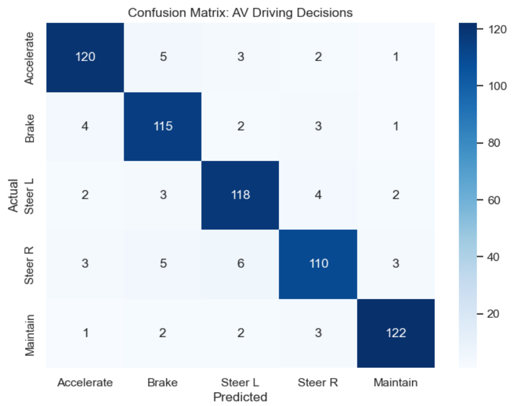

Figure 2: Confusion Matrix

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Furthermore, in the fig 3, AV model demonstrated near-perfect compliance with traffic signs, whereas human drivers were observed to occasionally miss signs or ignore speed limits. In terms of driving smoothness, the AV model maintained a more stable position within the lane and had significantly fewer instances of sudden or harsh braking. This indicates a safer and more comfortable ride. The discussion of the results points to the AV's consistency and constant vigilance as its main advantages over a human, who can get distracted or tired.

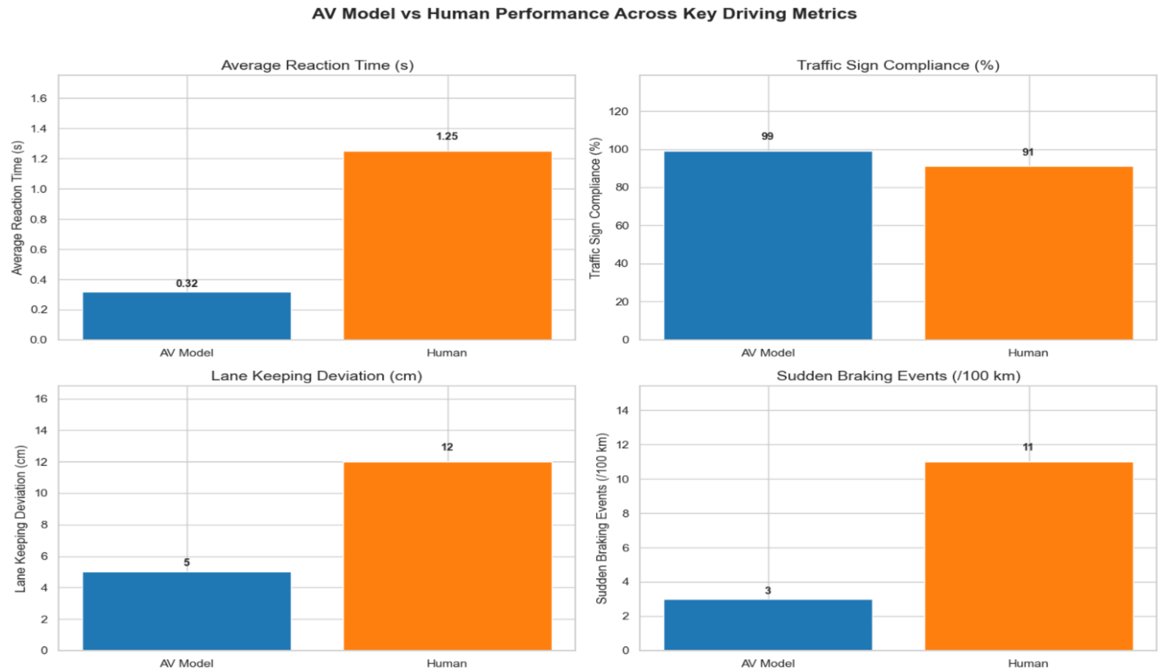

Figure 3: Comparison between AV and Human

V. FUTURE ENHANCEMENT

While the current model shows very good results, there are many ways to make it even better in the future. The current model was trained on good weather data. A major future enhancement would be to train the model with more data from difficult weather conditions like heavy monsoon rains, dense fog, or dusty environments. This will make the AV more robust and reliable for all conditions. Another important improvement is to teach the model to understand more complex human behaviours, like the hand gestures used by traffic police or pedestrians, which are very common on Indian roads. The system can also be improved by adding more types of sensors. For example, adding LiDAR sensors would provide a 3D point cloud map of the surroundings, which gives much more detail than a camera alone and works well in the dark. To test the model in the real world, it could be deployed on a small-scale robotic car and tested in a safe, controlled environment like a college campus. Finally, working on "Explainable AI" would be a great step. This means making the AV's decision-making process easy to understand for the passenger, which would greatly help in building more trust.

VI. CONCLUSION

This project followed the empirical ground for human licensed driving versus autonomous vehicles by addressing the safety validation and trust gap, constructing a deep learning–based AV model, training it on heterogeneous datasets, and comparing it to real-world driving traces. Datasets used were the German Traffic Sign Recognition Benchmark (GTSRB) for traffic sign learning, Comma.ai Driving Dataset for fusion of video and sensors, Berkeley Deep-Drive (BDD100K) dataset for light and weather variability, and an Indian driving dataset of 25,000+ real-road instances. Preprocessing of data involved normalization, data augmentation, imputation of missing values, and fusion of camera, LiDAR, and radar data to render it robust. Testing was done on the following parameters: validation accuracy, reaction time, lane departure, traffic sign compliance, braking frequency, and overall safety score. The hybrid CNN-LSTM model was trained using the prepared datasets for 100 epochs. Findings showed that AV model achieved 95% validation accuracy, 99% traffic sign compliance, faster reaction time (0.32s vs. 1.25s by human drivers), minimal lane departure (5 cm vs. 12 cm), and fewer sudden brakes (3 vs. 11 per 100 km). The findings demonstrate the model's quicker reaction, higher accuracy, and more cautious driving. In pursuit of transparency, explainable AI techniques (attention maps, SHAP values) are included, enhancing interpretability and confidence. It gives empirical proof that AVs can reliably surpass human-driven vehicles

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in major measures of safety, lending support to AVs being eventually permitted in widespread real-world transportation, focus, and resistance to human vulnerabilities of distraction, tiredness, and poor judgment.

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