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A Constructive Role for Social Science in the Development of Automated Vehicles Based on LFM-BiGRU Approach

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***Abstract* – This proposed system delves into the transformative realm of autonomous vehicles, a technological marvel that has captivated society's anticipation for its profound societal implications. While existing social science research predominantly focuses on regulatory, safety, and efficiency considerations, this method contends that these discussions fall short in comprehensively appreciating the extensive social ramifications of autonomous vehicles. Addressing this gap, the system aims to provide a more nuanced understanding of the broader societal impacts that autonomous vehicles are poised to instigate. The proposed methodology comprises three integral modules: preprocessing, feature extraction, and model training. Preprocessing involves essential tasks such as punctuation removal, URL elimination, and batch normalization. The feature extraction stage leverages TF-IDF, contributing to the discernment of significant features. For model training, the paper employs the LFM-BiGRU architecture, a distinctive aspect of the proposed method. Comparative analysis against conventional approaches, namely BiGRU-LSTM and BiLSTM, underscores the superior performance exhibited by the proposed method. This suggests that the LFM-BiGRU approach holds promise for advancing the capabilities of autonomous vehicle research and, consequently, societal understanding of this groundbreaking technology.**

Keywords— Electric Vehicle Charging System (EVCS), Electric Vehicle (EV), Normalization.

I. INTRODUCTION

Autonomous vehicles' (AVs) revolutionary ability to increase transportation accessibility and safety has been a hot topic recently. An essential aspect of creating and implementing AVs is testing and evaluating their driving intelligence. This reveals how well the AV can execute without human input. Currently, human-driven vehicle testing procedures like FMVSS1 and ISO 26262 only address safety-related system components, design elements, and regulations. But when it comes to driving tasks, these processes don't consider driving intelligence. So far as the authors are aware, there isn't currently a standard procedure for assessing AVs. There has been a lot of research into AV testing in recent years from academic institutions, professional groups, government agencies, and AV developers, but not enough theory or processes to support this testing and evaluation Numbers. The present gold standard for testing AVs, makes use of the agent-environment framework to integrate software simulation, closed-track testing, and on-road testing. The basic concept is to put autonomous vehicle agents through their paces in a simulated road environment, record their performance, and then compare it to human drivers. The past several years have seen a plethora of productive research into CAVs, or networked and autonomous vehicles. Central to ITS is the system of networked vehicles that can communicate with one another and the communications infrastructure to share important data (including traffic and road conditions) and safety warnings. The advancement of deep learning (DL) and other machine learning (ML) techniques is a driving force behind CAVs because of its widespread use in decision making. When compared to conventional linked vehicles, autonomous (self-driving) cars excel in two areas: task automation and collaboration. Many people think that autonomous vehicles will change the way people live and drive in future smart cities. The phenomenon of linked autos is made possible via automotive ad-hoc networks, or vehicular networks. Over the years, many variations of linked vehicles have been developed. Temporary infrastructure-to-vehicle (I2V) connections, unconstrained channel access delays, and non-guaranteed quality of service (QoS) were among the many problems with these systems brought to light in a recent study. Autonomous and manual cars work together in an ITS, but their unique strengths and weaknesses mean that the system's resilience, security, and safety can be compromised in unanticipated ways. A "smart city" is built upon a foundation of intelligent transportation, intelligent housing, intelligent landscapes, intelligent businesses, intelligent administration, and intelligent residents. The success of smart cities depends on smart transportation. Threats to smart mobility from cyberspace are expanding at a rapid pace. Two security researchers found critical flaws in autonomous cars. The researchers were able to control the primary functions of a self-driving Jeep from a distance. The car could be stopped from a distance even as it was travelling on the highway. And to top it all off, Keen Lab used zero-day assaults to compromise BMW and Tesla self-driving cars by taking advantage of browser and Wi-Fi vulnerabilities. Attacks and countermeasures against autonomous vehicles have been the subject of numerous studies, although comprehensive assessments are scarce.

II. LITERATURE SURVEY

More people and more automobiles are what cities need, says URBANISATION. Overloaded transport infrastructure that was constructed and improved upon a long time ago is a problem that every passenger must contend with. [1] Researchers are concentrating on ways to increase the capacity of existing transport infrastructures. Connected and automated vehicles (CAVs) are widely believed to have the potential to improve traffic flow through the integration of numerous communication networks. Concepts like Cooperative Adaptive Cruise Control (CACC) and Vehicle to Vehicle communication (V2V) [2] have been put up as foundational ideas for CAVs. Still, this method finds the smoothed trajectories by utilizing a final status that is known at a moment run an optimization procedure at junctions in an iterative fashion. Using the procedure to make a greatest way to proceed in a predetermined situation. This method may not be applicable because it cannot optimize in the absence of a final state. Several academic disciplines have also focused heavily on state-of-the-art machine learning tools. Reinforcement Learning (RL), a subset of this family, has demonstrated potential in playing video games [3] and board games against human players. It was thought that a learning-based paradigm might be developed to teach vehicles the correct controller from the beginning, according to car following theory [4]. It is feasible to construct new driving habits during learning that are more efficient than those passed down from humans. Instead of trying to recreate an old car-following model for CAVs, RL does extensive testing of many different action combinations, learns more about trajectories than a person could, and gets around the old model's empirical limitation [5]. A wide range of development stages are covered by autonomous driving systems, from early simulations to full-scale on-road testing and implementation. Their long-term effects on the economy, society, and the auto industry are uncertain. [6] Testing of Advanced Driver Assistance towards Automated Driving: A Survey and Taxonomy on Existing Approaches and Open Questions investigated a wide variety of testing methodologies, such as augmented reality, X-in-the-loop, and simulation-only approaches procedures, together with assessment criteria and metrics. [7]proposed fault injection as a solution to some of the issues the system found with testing way to improve the efficiency of scenario testing. Publications Challenges in Autonomous Vehicle Testing and Validation[8] go into detail about the problems with safety validation for autonomous vehicles and argue that, due to cost and methodological considerations, virtual testing should be the main goal. Regrettably, no set procedures exist at this time for evaluating and validating autonomous driving systems. [9] This is due, in part, to the fact that many contemporary autonomous system designs incorporate ML components, such as Deep Neural Networks (DNNs), which are notoriously difficult to test and verify. Object detection and classification in Automated Driving Systems (ADS) typically makes use of ML components like DNNs. This process entails identifying and categorizing objects within CCD images and calculating their locations in relation to the vehicle [10]. To make the most of current urban transport networks, several vehicle technology developments have been proposed, such as networked and autonomous vehicles. The ability for vehicles and infrastructure control units to communicate and share data in real time is the basic premise of linked vehicles [11]. The ultimate aim of fully autonomous vehicles is to do away with human driver's altogether. Instead, these vehicles will be controlled by robots that constantly monitor their environment using various sensor technologies, rather than relying solely on human vision and hearing. Then, rather than human brainpower, the robots will use suitable computer algorithms and vehicle control mechanics to decide how to steer the vehicle. The development of traffic control systems has been severely hindered by the emergence of CAVs, which enable the real-time regulation and control of individual cars [12]. These CAVs pave the way for vehicle-based control systems that can mitigate or do away with the drawbacks caused by human drivers' incompetence, diversity, and lack of teamwork [13]. In a nutshell, a vehicle-based paradigm shift from the present reactive/aggregated/collective and non-cooperative traffic flow management paradigm is possible. Using deep learning to control vehicles has many benefits. Due to its capacity to learn from data and adjust to new situations, deep learning is highly suited to control problems in dynamic and complicated contexts [14]. Eliminating the need to repeatedly tweak each parameter while trying to keep performance in all conceivable conditions, developers can now simply declare the expected behavior and train the system to perform well and generalize to new contexts through learning with deep learning [15]. The application of deep learning to the control of autonomous vehicles has recently attracted a lot of attention for these and other key reasons. [16]A variety of sensor configurations are utilized by researchers; some rely only on camera vision, some use multi-sensor systems, and yet others control the vehicle using lower-dimensional data from ranging sensors.[17] A low-level controller, usually employing classical control techniques, is responsible for achieving the intended acceleration, for example, in some systems that are developed using a high-level controller. The control target is where this method diverges from others. [18] Some drivers aim to become experts in every aspect of the craft, from basic observational skills to the ins and outs of the vehicle's low-level control interface. Even with the most cutting-edge active safety technologies in cars, these results suggest that driver conduct is the most critical factor causing road accidents. [19] In an endeavor to understand, characterize, and, ideally, predict traffic drivers' behaviors, numerous models based on different methodologies have been proposed by researchers over the past forty years. The fact that many personal factors, like as gender, age, experience, aggression, etc., [20] influence driver conduct makes driver modelling a difficult problem to solve. Perhaps developing autonomous vehicles would be the most effective means of reducing the number of traffic accidents. A major milestone on the road to creating completely autonomous cars would be this. Unlike human drivers, autonomous vehicles don't need to be told where to go or what's around them. [21] A variety of sensing technologies, such as computer vision, localization, ultrasound, lidar, and radar, are employed to do this.

III. PROPOSED SYSTEM

The widespread use of private automobiles in Western civilizations began around one hundred years ago. Urban and transport policymakers realized decades later how crucial it was to avoid or lessen the negative impacts of this transportation technology. There will be major shifts in how people get about cities in the future due to automated driving technology. Potential AV-related long-term consequences are the subject of this Special Issue.

A. Preprocessing

Preprocessing included converting the tweets to lowercase and removing punctuation, URLs, and references to Twitter usernames. In accordance with these procedures, the dataset was cleansed of frequent, potentially useless terms like "and" and "the" (i.e., stop words). Common domain and standard English words such as "car," "autonomous," "self-driving," "automated," and "vehicle" made up the stop words list. Stemming the words to their root was the last step in the preprocessing. The qdapRegex package in R was used to finish the preprocessing processes.

In order to validate the search criteria, an initial manual check was carried out following the initial preprocessing. According to this analysis, only few of the recovered tweets mentioned the Tesla accident. In order to make the complete dataset and the reactions to the Tesla crash easier to understand, the proposed approach constructed a second dataset that only included Tweets that mentioned the crash [22]. A combination of a keyword search and human inspection led to the identification of the tweets regarding the Tesla crash. "New Jersey," "NJ," and "Tesla" were among the phrases utilized to identify the Tesla crash. By hand-analyzing the data, the proposed approach were able to identify these terms, which revealed that the location and vehicle type were the most frequently referenced in tweets about the Tesla crash.

1) Analysis of Frequency

The proposed approach looked at the datasets from other angles, such as the ratio of retweets to new tweets, the frequency of tweets by account, and the frequency of phrases inside the tweets. An approximation of the communication drivers and the sort of communication surrounding tweets can be found in the tweets by account. One indicator of the ratio of unique to recycled content is the number of retweets, a function of Twitter that lets users repost the Tweets of other users on their own account.

2) Batch Normalization

Altering the starting weights or slowing down the learning rate are two ways to shorten the training phase. A significant complication to learning is a layer's reliance on its preceding layers. Any modification made to one layer can have a magnified effect on the ones that follow it. This training-based latency problem was effectively addressed by batch normalization. By standardizing the inputs per layer, this method improves the speed and stability of deep neural networks. To accomplish the standardizing and normalizing tasks, a new layer is applied to the output of an earlier layer. Finding the average and dividing the batch by its standard deviation are both steps in the procedure. Following this, the mean is subtracted and the total input is divided using the standard division and the smoothing term (ε). By preventing a division by zero, the smoothing term (ε) guarantees numerical stability in the process. Backward propagation updates the trainable parameters gamma and beta, which are the standard division and the mean, respectively.

B. Extraction of features

The feature extraction technique is crucial for obtaining features, which are significant words, from text data. This study examined various feature extraction approaches to help choose the one that is most suitable. Among the four feature extraction approaches, the most used in natural language processing (NLP) is Word2Vec, while bag-of-words and the term frequency-inverse document frequency (TF-IDF) model are also viable options [23]. Since the TF-IDF model can convey the relative value of each word in a certain document, it was chosen for this system because it is the most popular NLP model. Instead of just giving more weight to words that appear more frequently, the TF-IDF model can also take into account how often the system appear in the document as a whole. May see a TF-IDF model in Equation (1).

$$TF-IDF_{(s,j)} = TF_{(s,j)} \times \log\left(\frac{p}{DF_{(s)}}\right) \qquad (1)$$

in which $TF_{(s,j)}$ is the total number of words in documents j, p is the total number of documents, and $DF_{(s)}$ is the total number of documents that contain words (s) . This system analyzed data from urban arterial highways and intersections using the TF-IDF model to derive features and TF-IDF values. Area names, proper nouns, and vehicle names were deleted as the system were not relevant attributes to be derived. The next step in deducing the traits' significance was to classify them according to target objects, manoeuvres, inciting events, etc.

C. LFM-BiGRU Model:

1) LFM based decomposition of matrix

The latent factor model expands upon content-based filtering in important ways. Before making product recommendations to consumers, LFM sorts all things into categories according to the user's interest. The conventional LFM is shown by the matrix decomposition. Next, $z_{e,b}$ creates a ratings matrix with objects as columns and users as rows. When the after multiplying the the complete rating matrix is generated by merging the user's latent factor matrix with the literature's latent factor matrix. The mathematical terminology for representing a matrix as a product of two matrices is simply "decomposing" the matrix into its constituent elements. Modelled here is user i's evaluation of item b:

$$z_{e,b} = n_e m_b = \sum_{b=1}^{H} n_{e,v} m_{b,v}^{O} \qquad (2)$$

where $n_{e,v}$ represents the user's interest in connection to the v -th latent factor and $m_{b,v}^{O}$ represents the item's relationship to the v-th latent component. Here, z represents how much the product interests the user and H is the quantity of hidden components.

The user's expected rating for the research papers that are being considered is represented by the inner product of the two latent component matrices, which are initially constructed at random on the divided training set. When dissecting a latent factor matrix, this is one of the steps involved [24]. As a training set's actual ratings deviate from their expected ratings, the mean square error measures how far off the target set is. There is a continuous fluctuation in the scores of comparable research articles within the same class in the dataset since user interaction records for items are frequently concentrated in one or more classes. As a result, the proposed approach reduced the number of iterations by adjusting the bias $z_{e,b}$ according to the initial loss function. K is the expression for the loss function floss.

$$d = z_{e,b} - \sum_{v=1}^{v} n_{e,v} m_{b,v}^{O}$$

$$f_{loss} = \frac{1}{2} \sum_{(e,b)\in V} (d)^2 + \frac{\varepsilon}{2} \sum_{v=1}^{v} \left\| n_{e,v} \right\|^2 + \frac{\varepsilon}{2} \sum_{v=1}^{v} \| q_{i.k} \|^2 \quad (3)$$

when the prejudiced phrase To avoid overfitting, the regularisation terms required in the previous formula are represented by $\varepsilon\left\|n_{e,v}\right\|^2$ and $\varepsilon\|q_{i.k}\|^2$. $B_{e,b} = \frac{i_{e,b}}{\tau}$ represents how many times users have interacted with the item and an average of all user ratings b. represents the regularization parameter that, depending on the use case, must be determined via iterative tests. Using a stochastic gradient descent approach, the loss function is optimized.

$$c = B_{e,b}\left(z_{e,b} - \sum_{v=1}^{v} n_e v m_{b,v}^{O}\right) m_{b,v}^{h} - \varepsilon n_{e,v}^{h}$$

$$n_{e,v}^{h+1} = n_{e,v}^{h} + \beta(c) \quad (4)$$

$$m_{e,v}^{h+1} = m_{e,v}^{h} + \beta(c) \quad (5)$$

The parameters are optimised continually by iterative calculation (with the number of iterations chosen by the user) until the system converge. At last, the proposed approach get the user's interest preference $N_{e,v}$ and the latent component matrix found in the literature$M_{b,v}$

2) BiGRU Based Word Sequence Coding

Important for real-world applications, reverse text sequences reveal accessible mining-potential semantic information, whereas most GRUs can only extract forward semantic information from text sequences. To achieve a more thorough and precise text sequence encoding, the proposed approach use a BiGRU to represent both the forward and backward sequences of the textual content found in the literature at the same time. With some modifications to the GRU network architecture, BiGRU becomes a bidirectional neural network rather than a one-way feedforward network. Because of this, it can store the literature context in two ways, giving different weights to each time step. At least for the time being, the proposed approach can have a better grasp of the literature features by merging the hidden states of the two networks into one, which the proposed approach will call the bidirectional network's hidden state.

Storage space requirements for BiGRU are double that of storing a single layer due to the simultaneous storage of weights and offset values for both hidden levels. During the training process of the GRU network, the proposed approach input the word vector sequences produced by the BERT model and adjust the hidden layer dimension. Don't need to tell GRU how many time steps to use because it does its own iteration. To minimize the mean square deviation of both the hidden state sequence and the literature latent component matrix, the proposed approach use the label from the training set, which is the literature latent factor matrix learned in the LFM. Afterwards, the proposed approach train the model using the Adam method for small batch gradient descent, which updates the parameters of the model constantly until convergence.

3) Attention Mechanism Based Pooling Technology

The real-world application of the BiGRU model will result in a skewed final feature vector towards the end of the text, caused by the lengthy word sequence in this study's text. The proposed approach address this issue by presenting an attention mechanism that may utilize user input to modify word vector weights, resulting in a more precise and succinct depiction of content attributes. The concept of automatically producing text feature vectors is the foundation of the user attention method in this method. Each word's significance in the text sequence and the extent to which user latent characteristics impact them will determine the weighting of these vectors. This is the fault of the attention network. A weighted average of word vector sequences is used to represent text feature vectors in the literature. Future suggestion assignments will benefit from the generated text feature vector since it more accurately reflects user preferences while maintaining the literature's linguistic content.

The word sequences f_o learnt by the word encoder based on the BiGRU network and the user latent factors n_e learned by the shallow LFM are inputs to the user attention network. In the hidden state, the first step is to linearly transform pu and f_o at time o using the weight matrices $S^{(e)}$ and $S^{(f)}$, respectively. After that, the nonlinear semantic information is extracted using the nonlinear activation function. Lastly, the user's attention level with respect to word t in the text sequence is determined using linear transformation once again. This is the formula that will be used to calculate it:

$$z_{e,o} = z_{(n_e,f_o)} = k^{O} \tan f\left(S_{n_e}^{(e)} + S_{f_o}^{(f)}\right) \quad (6)$$

the user attention network can learn the vector v, the weight matrix $S^{(e)}$, and $S^{(f)}$. For each user e, the normalization procedure yields the weight $y_{e,o}$ that e has given to word o in the text sequence, based on the degree of attention u has shown to that word. The novel literary latent components retrieved from the material are represented by the weighted average $m_e = \sum_{o=1}^{O} y_{e,o} f_o$ of the word vector sequence, in line with the weight value that the user attention network produces. Substituting latent components from more recent literature for those from older literature is the next stage.

IV. RESULT AND DISCUSSION

The roads of the United States and countless other countries are already occupied by automated vehicles (AVs). The proposed approach are currently living in a world where autonomous vehicles are a reality, thus the questions around their implementation have shifted. Instead, people are increasingly wondering if these systems should be completely automated or if the system should be subject to some type of direct human management, and how these technologies will affect social world, transportation systems, and the people who live in it. The more pressing question is how transportation will evolve in response to the gradual dominance of these autonomous operational cars on roads. How will scientists and the many social media platforms keep the public informed of their growing capabilities, and how will research itself influence these changes? The proposed approach hope to solve these difficulties and maybe anticipate some new ones by offering some solutions here.

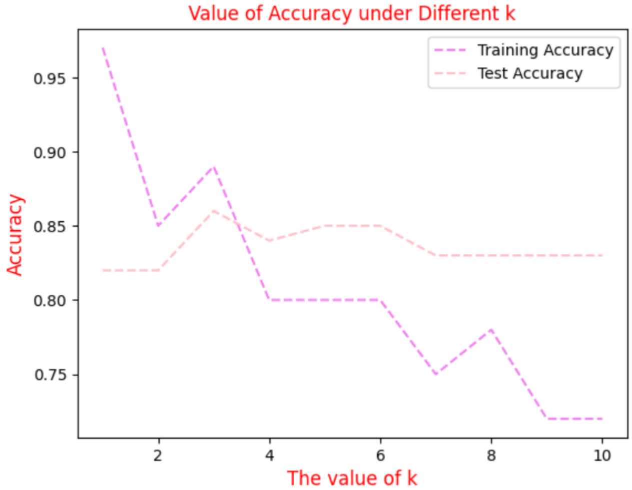

Fig. 1. Value of Accuracy Under Different K

Regarding the LFM-BiGRU approach, k is a crucial parameter that dictates the classification outcomes. As you can see in Figure 1, the accuracy of the categorization with various k

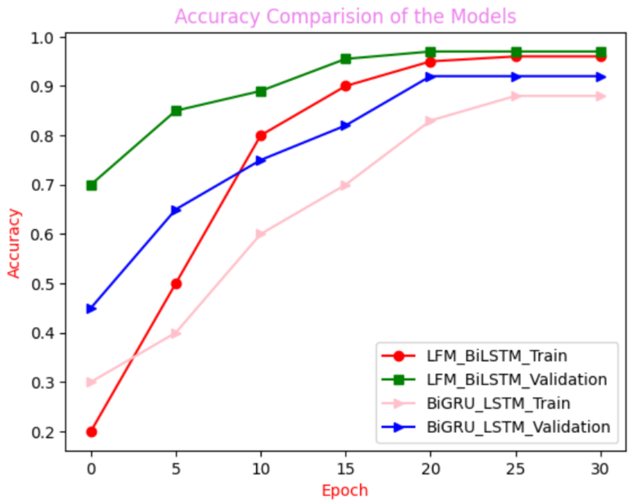

Fig. 2. Compared accuracy (training and validation) of LFM-BiLSTM and BiGRU-LSTM machines, accuracy improves with more epochs.

Figure 2 also shows a comparison of the two methods' accuracy. Like the loss function, the combined FRM-BiGRU model is about twice as accurate as the basic BiGRU-LSTM model. As the number of training epochs increases, accuracy improves for both models.

The implementation of coupled LFM-BiGRU results in an improvement to the loss function of the BiGRU-LSTM architecture for each epoch, as demonstrated in Figure 3. In addition, the amount of loss reduces in a consistent manner as the number of training epochs increases.

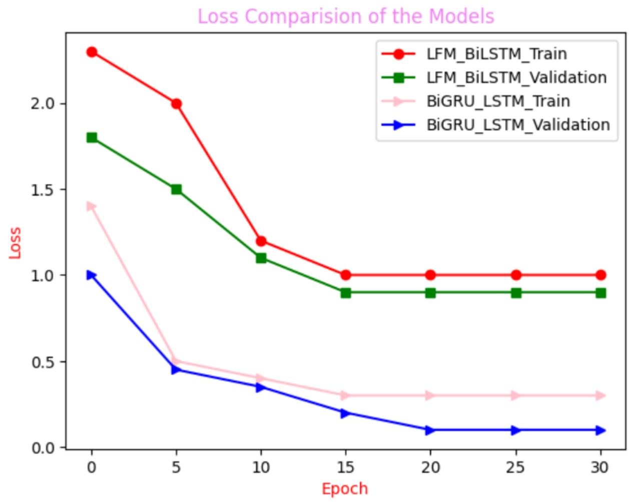

Fig. 3. Compared Loss (training and validation) of LFM-BiLSTM and BiGRU-LSTM

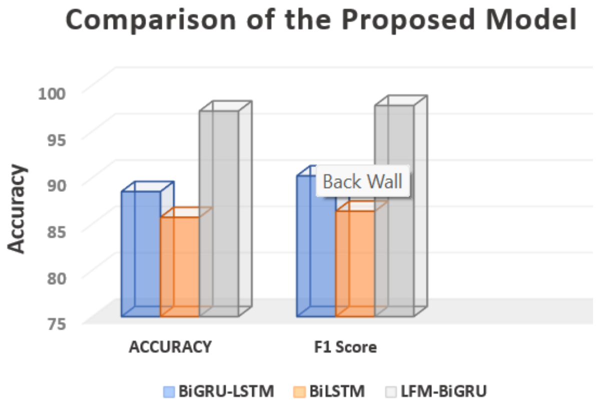

Fig. 4. Identification accuracy and F1-score of different algorithms in test data

To be more specific, the proposed approach discovered that the LFM-BiGRU model outperforms two well-known machine learning models, the BiGRU-LSTM and the BiLSTM models, with an accuracy and F1-score of 97.2% and 97.8%, respectively (Figure 4).

V. Conclusion

To sum up, the topic surrounding autonomous automobiles has expanded beyond its original scope, involving a wide range of stakeholders including insurance experts, urban designers, parliamentarians, social scientists, and legal experts, among many others. Numerous technological and systemic developments have supported the creation of completely autonomous cars. A critical foundation for articulating the different degrees of autonomy and distinguishing between human and machine-performed jobs has been the introduction of automation levels. Turning attention to the methods the proposed approach have described, the proposed approach begin with a thorough preparation step that gets rid of unnecessary punctuation, URLs, and batch normalization. By utilizing TF-IDF for feature extraction and LFM-BiGRU for model evaluation, technique accomplishes the remarkable accomplishment of surpassing 97% accuracy. Even more impressive is the fact that it outperforms the well-established models BiGRU-LSTM and BiLSTM. Recommended strategy has the potential to make a substantial contribution to the developing field of autonomous vehicle research, as these data demonstrate its efficacy.

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