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Iot-Based Road Abnormality Detection Using Ai/Ml Techniques

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Abstract: **-**The condition of the road network plays a vital role in affecting rolling resistance, driving comfort, and road safety. Consequently, it is imperative to regularly and meticulously inspect the road infrastructure to identify any areas of damage or potential hazards. Based on car sensors and supervised machine learning categorization, techniques have been developed to thoroughly and automatically digitise the road infrastructure and evaluate the condition of the road. One classifier cannot be used to other cars since different types of vehicles have varied suspension systems with unique reaction capabilities. The process of gathering training data for each unique vehicle and classifier often takes a long time. To solve this issue, a dataset of inertial sensors data for Road Surface Type Classification (RSTC) from Kaggle has been used. The findings demonstrate that the best algorithm for reliably transmitting road surface data from a single vehicle to the cloud using IoT is the long-short term memory (LSt-TMem), which is based on the performance of the Support Vector Machine (Sup-Vt-Mac) and long-short term memory (LSt-TMem). Additionally, this approach provides the opportunity to combine the output and data on the road network from many aberrant locations, allowing for a more accurate and reliable forecast of the ground truth.

Keywords*: Road, abnormality, detection, Internet of Things (IoT), artificial intelligence (Art-Int) / machine learning (Ma- Lern)*

1. Introduction

The safety of humans on road has become a serious concern in central and southern parts of Asia [1]. Between 2015 and 2018, the World Health Organization (WHO) estimated a 60% increase in road fatalities in central Asia [2].In India, the Ministry of Road Transport and Highways, under the Government of India, considers various road conditions such as zig-zag roads, S-curves, steep slopes, narrow slopes, road junctions, sharp curves, railway overbridges, and T-junctions. Hence, various road safety awareness campaign and their issues are promoted by the Indian government based on the road safety information database, safer road infrastructure, building more safer vehicles, improving competent capabilities within drivers, increasing the quality of road infrastructure, safety education, and the training of road medical services. However, despite substantial road safety precautionary measures, there was a 29% increase in road mishaps and fatalities between 2010 and 2016 in India [3]. Therefore, not only the shape of the road is important but also the type of road condition decides the extent of road abnormalities.

Authorities are grappling with the challenge of identifying common road irregularities such as speed breakers, potholes, and worn-out roads. In this context, IoT and automobile-dependent sensors, including gyroscopes and accelerometers, play a crucial role in detecting these abnormalities [4]. Gyroscopes are instrumental in achieving dynamic stability and maintaining the angular velocity-based orientation of the vehicle. These sensors also measure vehicular acceleration, direction, and speed, providing insights into various accelerating and braking forces [5]. These forces serve as responses used to measure anticipated or unanticipated road abnormalities.

Due to recent fast technological improvements, reliable sensors including gyroscopes, accelerometers, GPS, electronic compass, microphones, cameras, etc. have been miniaturized and integrated into mobile devices. The method of pothole detection using mobile devices is cost-effective and efficient due to the widespread use of mobile phones and the absence of specialized installation requirements. This study used real- time data gathered from mobile devices to identify speed breakers, potholes, and worn-out roads. The majority of current methods for detecting potholes are less accurate, require specialized and expensive technology, or are not reliable enough to identify road abnormalities in the real world.

2. Related Work

Over the past few years, a number of speed breakers, potholes, and worn-out road detecting methods have been suggested by various researchers [6]. Speed breakers solve the purpose of reducing the speed of vehicles with minimum damage to them. The speed breakers can withstand maximum impact because it is made of asphalt, concrete, PVC, or rubber. Similarly, in the case of potholes the issue of determining the depth of it when covered in water, sand, pebbles, or small stones. It can be categorized as follows:

- “Normal / run-of-the-mill pothole
- The pseudo pothole
- The edge
- The manicured pothole
- The camouflage pothole
- The scattershot
- The trench
- The pot road” [7]

Moreover, various abnormalities like oil spillage or spots on the road, manholes cracks, rutting, uneven swelling and depressions of asphalt-type roads due to heating temperature, and overgrown grass, trees, and bushes on the road may suitably be proven hazardous at times if not detected priorly [8]–[10].Hence, due to these abnormalities, the speed breakers, potholes, and worn-out roads detection techniques, may be divided into following methods.

2.1 Vibration-based methods

Various known equipped sensors like, ultrasonic, gyroscope, and accelerometer are useful for measuring the distance between the vehicle’s bonnet section-to-road, acceleration, deceleration, and angular orientation of the vehicle [11], [12]. The rapid generation of these types of reading can be interpreted based on the amplified output with respect to time. As a result, the accelerometers used in the vibration- based techniques and gyroscopes used for determining the orientation of the vehicle are often considered from a mobile device. In a study conducted by researchers in [13], they employed this approach to evaluate the efficacy of various threshold-based methods using data obtained from z-axis mobile sensing. Based on a restricted sample, the authors argue that the actual positive rate is equal to or greater than 90%. A threshold-based technique was also used by [14], [15].

2.2 3D reconstruction-based methods

In reference [16], a pothole identification method based on machine learning was explored. This approach utilized features extracted from crowdsourced sensor data obtained from a limited number of undersampled simulated vehicles using CarSim. The authors reported an impressive simulated accuracy of 99.6%, but when tested in real-world scenarios, the accuracy dropped to 88.9%. Replicating their method of integrating simulated data from 500 cars into real-world conditions poses challenges due to factors like inaccuracies in GPS data, missing data points, variability in sensor configurations, and complexities in generalizing the simulation.

In a study cited as [17], a comparison was made between the performance of two machine learning techniques: Support Vector Machines (SVM) and gradient boosting. The study employed data collected from an iPhone 6S, including 21,300 accelerometer and gyroscope measurements, as well as 96 instances of potholes encountered during a single vehicle's operations. The authors assert that both gradient boosting and SVM with a radial basis function (RBF) kernel achieved the highest accuracy, achieving 92.9% and 92.02%, respectively. However, it is important to note that the achieved recall (0.42) and accuracy (0.78) were notably lower in this study.

2.3 Vision-based methods

According to reference [18], the camera represents the most commonly used vision-based approach for video surveillance and for monitoring applications related to vehicles. The road anomalies depicted in references [19]–[21] serve to notify drivers about irregularities on the road and also provide information about these abnormalities across larger road areas. This is achieved by utilizing GPS location data along with the depth of the pothole, expressed as a percentage.

The approach based on images or vision involves the use of cameras to capture images or videos of road features such as speed breakers, potholes, and deteriorated road surfaces. These images are then utilized to gather data. Several techniques related to image processing have been employed by various researchers, as seen in references [22]–[25], particularly within a restricted dataset for the identification of potholes.

Certain researchers, as cited in references [26]-[30], have combined surface and geospatial information from camera images to train deep neural networks. A total of 969 images were employed to evaluate the model's performance, yielding a precision of 92.4%, recall of 93.8%, and an F-score of 93.0% as outcomes. It's worth noting that this method demands significant computational resources, which hampers its feasibility for real-time detection.

The majority of research in the field of speed breaker, pothole, and worn-out road detection has heavily relied on image-based methods. These methods utilize databases of actual road anomalies as references. However, any changes in the size of speed breakers, potholes, road markings, or even the presence of dirt on the road can impact the accuracy of non-machine learning models. The computational demands of this approach require substantial processing power, making real-time detection of speed breakers and potholes impractical.

Alternatively, the threshold-based technique offers a simpler approach to detecting both types of road irregularities. However, determining suitable threshold values through heuristic methods can be labor- intensive and prone to human error. Furthermore, extending the model's performance to different road surfaces, vehicles, or pothole sizes might prove challenging.

Many existing methods for speed breaker and pothole detection rely on specialized and expensive technology, exhibit lower accuracy in identifying potholes, or lack the reliability to detect all types of potholes. Additionally, some models emphasize accuracy as a performance metric, which is often mistaken for overall improved model performance. Earlier research showcased the difficulties they faced in accurately detecting potholes, with higher accuracy but considerably lower precision and recall scores.

In light of these challenges, this study conducts a comparative analysis of machine learning models employing Support Vector Machine (SVM) and Long Short-Term Memory with Temporal Memory (LST-TMEM) approaches for detecting speed breakers, potholes, and worn-out road sections. The utilized dataset is sourced from the RSTC dataset on Kaggle [31]. The resulting data is then transmitted to the cloud for further logging, acquisition, and data visualization.

3.ProposedRoad Anomalies Detection Approach

The exhaustive work on constructing fine-grained data sets with uniqueness in their type is freely available in [31]. The distribution of pothole depth magnitudes that make up the data set is shown in Figure 1. Figure 2 illustrates roughly how the highest difference between the pavement level and the depression's lowest point was used to calculate a pothole's depth. A measuring tape was employed to get the precise value of depth (ground truth). The reading was obtained at pavement level with the hook positioned at the pothole's lowest point. Given their impact on the car's suspension, speed breakers made of metal or asphalt can be thought of as the same sort of artifact. However, the material they are composed of may have an impact on the sensor signal in a different way.

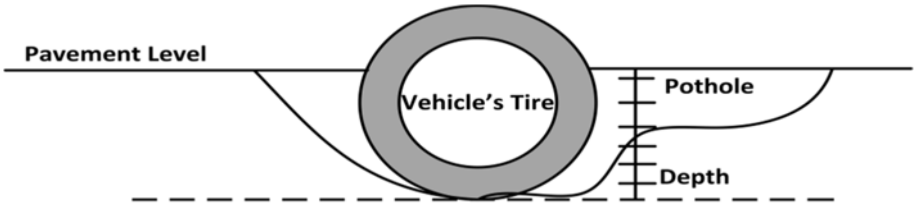

Figure 1.Schematic illustration of the depth of a pothole

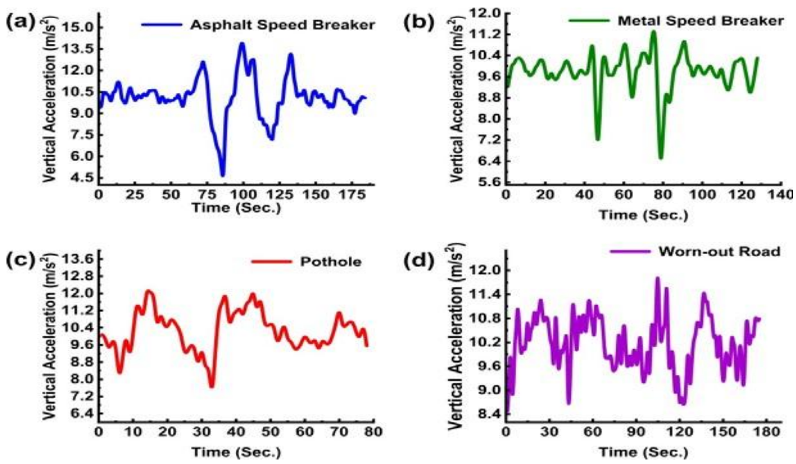

Figure 2.Vertical acceleration of (a) asphalt and (b)metal-based speed breaker, (c) potholes, and (d) worn-out road abnormalities

3.1 Signal Pre-processing

To produce vertical acceleration (parallel to gravity), all signals have to be reoriented as a preparatory step, as detailed in [30]. Only data from the vertical axis was required for this study.

3.2 Setting-up experimental road abnormalities using the proposed method

The unique inference issue will then be modeled using three distinct learning schemes since one of our goals is to contrast various learning problems and stimulate discussion about the optimum course of action. The two classification models— Sup-Vt-Mac and LSt-TMem – are compared in this study for their performance.

3.2.1 Sup-Vt-Mac

Support Vector Machines (SVM) operate by defining a hyperplane within an N-dimensional space, where N denotes the number of features. This hyperplane acts as a decision boundary, aiding in the classification or separation of data points. The characteristics of the hyperplane, such as size and orientation, are contingent on the number of features present. When dealing with two classes, the SVM algorithm identifies a hyperplane that not only minimizes a metric associated with misclassification errors but also maximizes the margin – the space between data points of distinct classes. This methodology enhances the model's robustness in reducing classification errors.

In scenarios involving binary classification tasks, SVM strives to locate the optimal hyperplane that maximizes the margin between data points of both classes. To achieve this, a positive regularization parameter labeled as "C" is introduced. This parameter governs the trade-off between expanding the margin and achieving low training or test errors. Smaller "C" values prioritize a wider margin even if it entails some misclassifications. Conversely, larger "C" values prioritize minimizing misclassifications, even if it results in a narrower margin.

When linear separation of data isn't feasible, SVM can leverage "kernels" to establish a hyperplane/feature mapping with a nonlinear boundary. Kernels facilitate the transformation of data into a higher-dimensional space, where linear separation might become feasible. This attribute equips SVM to handle intricate classification challenges characterized by nonlinear decision boundaries.

3.2.2 LSt-TMem

LSt-TMem, which stands for Long Short-Term Memory with Temporal Memory, represents a distinct variant of a recurrent neural network (RNN) meticulously designed to tackle the pervasive issue of vanishing gradients commonly encountered in conventional RNN architectures. The hallmark of LSt- TMem is its incorporation of a memory cell alongside three gating mechanisms that meticulously regulate the ingress and egress of information within the cell. This notable divergence from traditional RNNs underscores the uniqueness of the LSt-TMem model. By implementing a memory cell and three gating mechanisms, LSt-TMem effectively circumvents the challenge of vanishing gradients that can hamper the learning process in standard RNNs. These gating mechanisms enable the model to capture and preserve crucial temporal dependencies, facilitating the comprehension of sequences and patterns within data more adeptly than conventional RNNs.

During each time step, LSt-TMem processes input data. The input gate updates the memory cell state based on the current input. The forget gate determines which aspects of the previous state should be disregarded, while the output gate controls the current state's output. In essence, LSt-TMem is adept at both remembering and forgetting information over extended periods, which makes it particularly suitable for handling sequential data. This capability is achieved by utilizing a memory cell and three gating mechanisms that manage information flow within the cell. Before extracting relevant features for training with a machine learning model, the raw sensor data from both applications undergoes preprocessing, combination, cleaning, and separation into training/validation and test sets. The research approach is depicted in Figure 3.

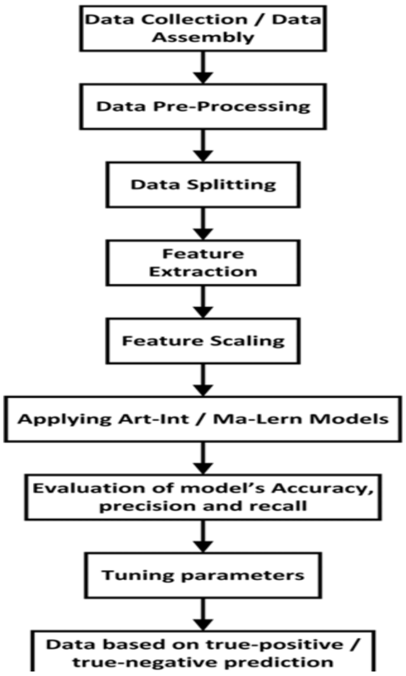

Figure3.FlowofAlgorithm

3.3 Feature Extraction

The moving window methodology entails the utilization of a window that encompasses the current raw data at a particular time and also includes historical data extending back to a specified point in time. This window is employed to calculate various statistical attributes at that specific time instance. Following this, the window is shifted forward in time, and this process is iterated until all the raw data has been processed. This approach allows for the analysis of data patterns and trends over successive time intervals while considering both immediate and past information. To avoid data leakage, measures were taken to ensure that different segments of the data did not overlap. The collected raw accelerometer and gyroscope data for each period were utilized to derive a comprehensive set of statistical features.

3.4 Data Exploration

Figure 4 illustrates the time domain representations of the x-, y-, and z-axes. This visual depiction highlights occurrences of potholes and non-potholes across all routes and cars involved in the data collection process. The noticeable abrupt variations in values within the time domain could be attributed to inaccuracies in sensor signals, leading to irregular data patterns.

To address the potential presence of signal noise and gain insights into the nature of these fluctuations, Figure 2 in the frequency domain can be consulted. Analyzing the data in the frequency domain can aid in identifying patterns of noise and disturbances that might be affecting the accuracy of the collected sensor data.

Figure 4. Server-based data logging system for Accelerometer Readings

3.5 Metrics for Evaluation and Cross-Validation

In this investigation, a range of performance metrics were employed to comprehensively evaluate the models, encompassing accuracy, precision, recall, and the F-score. The common metric of accuracy gauges the ratio of correctly predicted observations to the overall number of observations. However, its appropriateness relies on the distribution of false-positive and false-negative instances. In scenarios with balanced datasets, accuracy tends to offer a more accurate portrayal of model effectiveness.

Precision serves to quantify the ratio of accurately predicted positive observations to the total number of predicted positive instances. This metric becomes especially pertinent when the ramifications of false positives carry considerable weight. On the contrary, recall assesses the model's capacity to appropriately recognize positive cases from the entirety of actual positive occurrences. This metric becomes vital when the consequences of false negatives are significant.

To encapsulate both precision and recall into a unified measure, the F-score is adopted. The F-score delivers a comprehensive appraisal of model performance. This methodology is derived from a supplementary study [30]. Notably, utilizing the F-score perspective prevents the independent assessment of precision and recall, ensuring a more holistic evaluation. This diversified set of performance metrics provides a well-rounded perspective on the models' capabilities and limitations, considering factors such as overall accuracy, sensitivity to false positives, and sensitivity to false negatives.

To address class imbalance, the dataset was balanced using random under-sampling of the dominant class. This strategy ensures that the machine learning models are trained on an equal number of samples from speed bumps, potholes, and worn-out roads. Cross-validation played a crucial role in model development, contributing to the creation of a more generalizable model by reducing the potential for bias or variance. To create a unified training/validation dataset for the machine learning model, the individual datasets were consolidated into a single data source.

4. Analysis and Discussion

Table1.PerformanceMetric–TrainingDataset

Models		Accuracy	Precision	Recall	F-score	AUC
LSt-TMem	ForAsphaltSpeed Breaker	92.4%	87.4%	92%	0.88	0.94
Sup-Vt-Mac		84.5%	78.9%	81%	0.76	0.85
LSt-TMem	ForPotholes	89.6%	88.2%	93%	0.86	0.92
Sup-Vt-Mac		82.2%	79.1%	85%	0.78	0.86

Table2.PerformanceMetric–TestDataset

Models		Accuracy	Precision	Recall	F-score	AUC
LSt-TMem	ForAsphalt SpeedBreaker	91.8%	85.4%	90%	0.91	0.9
Sup-Vt-Mac		81.7%	76.7%	78%	0.82	0.86
LSt-TMem	For Potholes	90.4%	86.2%	89%	0.87	0.91
Sup-Vt-Mac		82.1%	75.9%	80%	0.79	0.87

The comparative effectiveness of LSTM and SVM models is visually illustrated in Figures 5 and 6, respectively, while Tables 1 and 2 provide a summary of their performance on both training and testing datasets. The dataset was partitioned into training and testing subsets, with Support Vector Machines (Sup-Vt-Mac) and Long Short-Term Memory (LSt-TMem) serving as the two binary classification machine learning models. These models were trained on 80% of the data and evaluated for their performance on the remaining 20%.

On the training dataset, the LSt-TMem model showcased superior performance, achieving an accuracy of 92.4%. As a result of further optimization through hyperparameter tuning, substantial enhancements were observed across accuracy, precision, recall, and F-score metrics for identifying speedbreakers. Notably, the LSt-

TMem model achieved a perfect accuracy score of 1.0, indicating consistent and accurate predictions of speed breakers, potholes, and worn-out roads.

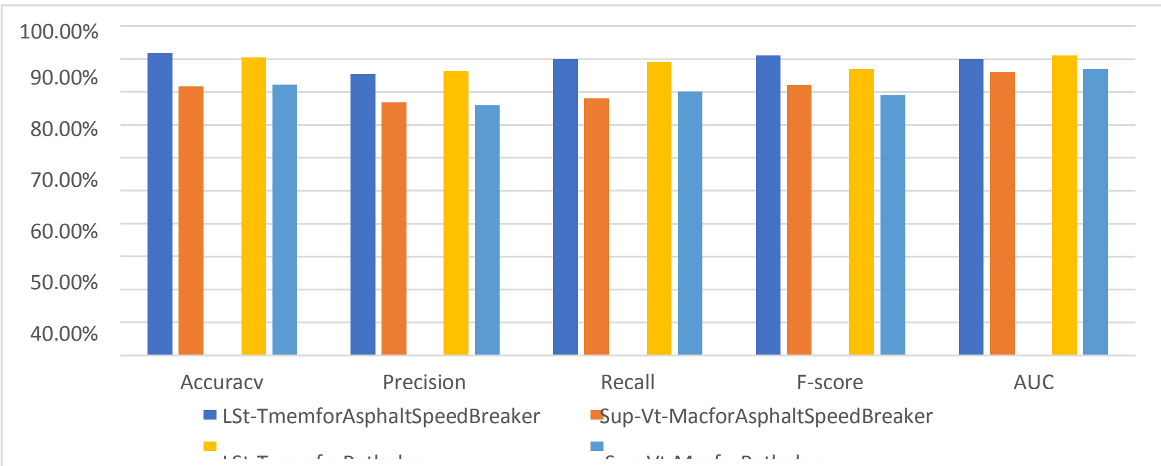

Figure5.Precision-recallcurveofthetestdataofLSt-TMemforTrainingDataset

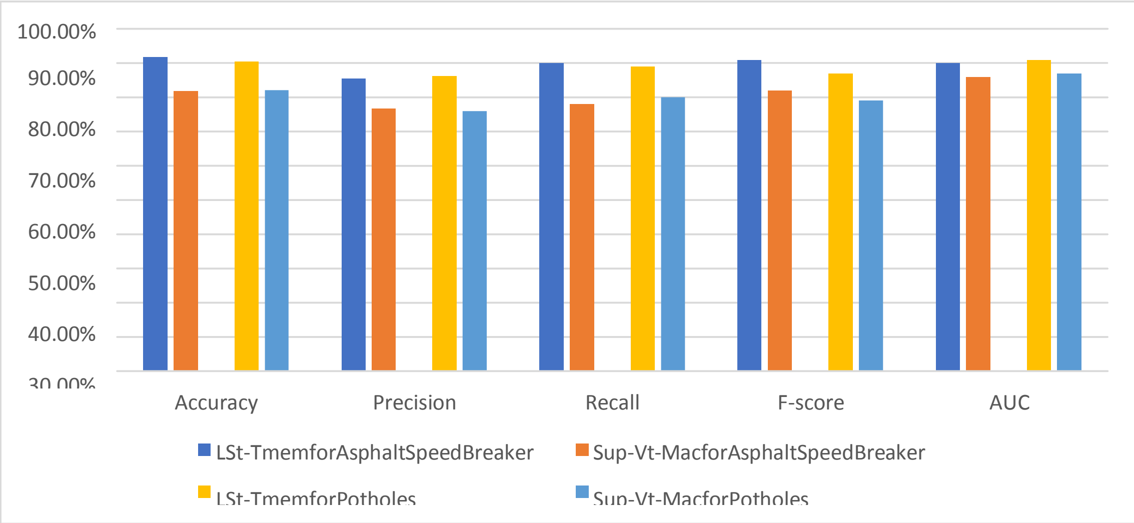

Figure 6.Precision-recallcurveofthetestdataofLSt-TMemforTestDataset

Following hyperparameter tuning, the LSt-TMem model outperformed the SVM model on the testing dataset. The LSt-TMem model achieved accuracy, precision, recall, and F-score scores of 91.8%, 85.4%, and 90.0%, respectively. The Area Under the Curve (AUC) score for the LSt-TMem model was not specified.The findings as a whole demonstrate that the LSt-TMem approach performs very well in terms of reliably and precisely recognizing different road irregularities, which demonstrates its efficiency in performing this specific job.

5. Conclusion and Future Scope

In the course of this research, a dataset obtained from Kaggle was utilized. This dataset specifically focused on categorizing road surfaces for locating speed breakers and potholes.In this study, we employed two different binary categorization machine learning models—Sup-Vt-Mac and LSt-TMem—to conduct a comparative analysis and assess their performance.Before proceeding with the feature extraction process, we separated the training dataset, validation dataset, and test dataset. The dataset was then balanced to ensure fairness. The LSt-TMem model exhibited the best performance on the training dataset, achieving an accuracy of 92.4%. After adjusting hyperparameters, the LSt-TMem model's accuracy, precision, recall, and F-score for identifying speed breakers improved to 92.4%, 87.4%, 92%, and 0.88, respectively. The hyperparameter optimization resulted in significant enhancements, as evidenced by accuracy, precision, recall, F-score, and AUC improvements of 91.8%, 85.4%, 90%, 0.91, and 0.91, respectively, on the test dataset for speedbreakers.

Additionally, the LSt-TMem model achieved a perfect accuracy score of 1.0000, indicating its ability to predict occurrences of speed breaks, potholes, and outdated roads with a hundred percent accuracy rate.However, owing to a considerable number of false negatives, the recall score was 89%. This suggests that the model occasionally misclassifies potholes as non-potholes, speed bumps as non-speed bumps, and worn-out roads as non-worn-out roads.

For future research, it is imperative to acquire diverse data encompassing various types of roads and vehicles to construct models that generalize well across different scenarios. Additionally, more comprehensive annotation will be required to develop a model capable of categorizing potholes with greater accuracy. This refined classification can enable road maintenance organizations to prioritize repairs based on the severity of potholes.

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