iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: X Month of publication: October 2025

DOI: https://doi.org/10.22214/ijraset.2025.74902

A Review on "Road Surface Anomaly Assessment Using Low-Cost Accelerometers: A Machine Learning Approach"

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Abstract: Mainly every developing or developed nation in the world faces a significant issue. in maintaining its road network and also factors like, apart from satellite assessment methods, mostly traditional methods, face a significant challenge for assessment, and assessments are not carried out frequently, so updating of data is also an issue. The authors of this review paper studied and critically analysed a first cost-effective solution for a road infrastructure assessment, which includes fault detection methods developed by Martinelli et al. (2022), the invention uses a data from inexpensive sensors like accelerometers that are mounted on vehicles, converts a signal in the time-frequency domain using the Short-Time Fourier Transform (STFT) and applies a machine learning classifier to identify the different types of asphalt deterioration in addition to locating them. It provides a system of documented components that starts with a collection of data, which are our accelerometer signals and extraction of features (Coefficient of Variation and Entropy) and results in damage categories, which highlights a potential of the system. The results using a support vector machine (SVM) classifier achieved an accuracy of up to 91.9%. In addition to that article discusses a potential application of it and future research areas
Keywords: Road Surface Monitoring, Accelerometer, Machine Learning, Signal Processing, Pavement Distress, Time-Frequency Analysis, Low-Cost System.

I. INTRODUCTION

Road networks and infrastructure are the soul of a country's economy, which carries both people and goods, and there are a lot of factors that contribute to the degradation of roads, which results in potholes, cracks, and rutting, which results to traffic and accidents, these flaws endanger users' safety and fun to drive [1, 2]. According to the paper under review, poorly maintained roads are the primary cause of the greatest number of traffic accident deaths globally because many users view them as a biggest safety risk. Although there are various traditional survey methods like visual Pavement Condition Index (PCI) for assessing road conditions are well established, but they are impacted by a subjectivity, low productivity, and risks an operator safety risk [3]. However, only a cutting-edge technology Solutions are in a small number, like 3D scanners and laser imaging systems can achieve high precision, but their high cost makes it very hard to use them widely and frequently, especially for a local government with a low budget [4, 5]. A cost-effective and scalable solution is needed for this purpose. The paper "Road Surface Anomaly Assessment Using Low-Cost Accelerometers: A Machine Learning Approach" authored by Martinelli et al. is closely related to this topic. It describes a system that utilizes cheap, commonly used accelerometers that are attached to standard vehicles. Their contribution is innovative not just in detecting the types of distress through time-frequency analysis-based features but also in classifying them by machine learning model. This review contains a detailed account of their approach, a critique of their experimental results, and a discourse of the system's generalizability and future potential.

II. METHODOLOGY OF THE REVIEWED SYSTEM

By segregating the Martinelli et al. system into three subsequent subsystems, it is possible to establish a coherent pipeline from the input of raw data to the output of classified data.

A. Data Acquisition and Pre-processing

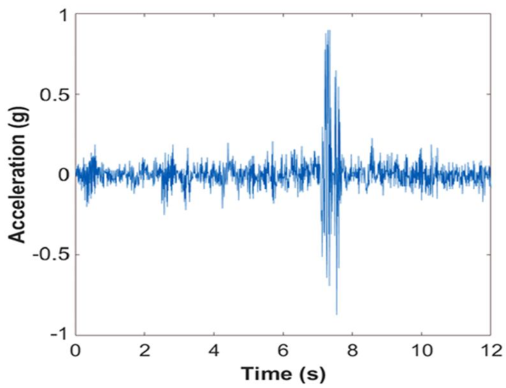
The hardware setup is low cost and based on an MPU6050 MEMS accelerometer and an Arduino Yuan platform, At 100 Hz, the Z-axis data is captured.

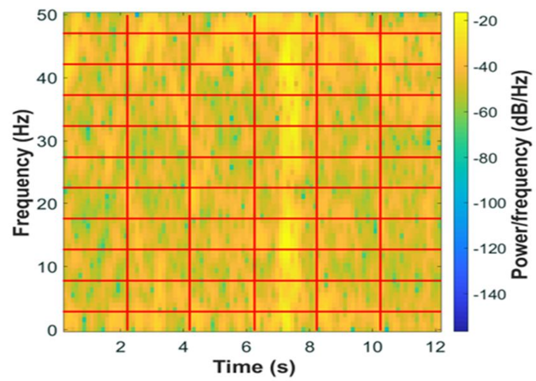
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue X Oct 2025- Available at www.ijraset.com

One important factor that needs to be considered is the mounted location of a sensor. which are the floorboard and dashboard of a car, the author clearly noted that the location of the sensor affects the signals and suspension system of a vehicle. as a complex filter. Because it is closer to the chassis, the floorboard produces a more direct and less muffled output of road vibrations than the dashboard.

B. Time-Frequency Analysis and Feature Extraction

The author decides to use Short-Time Fourier Transform (STFT) after recognizing that road irregularities result in non-stationary signals. The STFT operation shows the vibration in signal frequencies as a function of time because it is applied to the signal in brief, consecutive time windows (0.5 s with 75% overlap).The amplitude of the STFT, which is a grid of smaller blocks (65x100), is further divided into each block.





The feature extraction layer is the primary innovation. For each block of the STFT grid, the areal energy Ei,jEi,j is calculated. Two strong data global descriptors are extracted for the whole frame from this energy distribution:

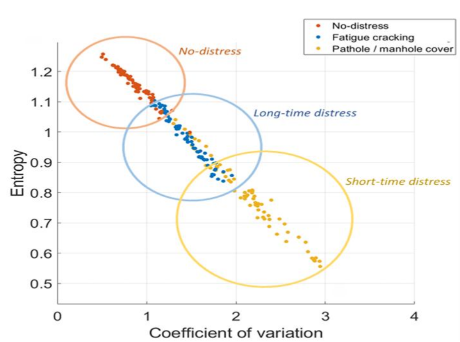
1) Variance coefficient (CV): It is defined as standard deviation divided by mean (CV=σ/μ). A high CV indicates a signal with high variability, which is characteristic of impulsive events like potholes.
2) Entropy (H): Entropy is a criterion for measuring the randomness or the unpredictability of the signal. A standard signal with noise, like a smooth surface of the road, carries a high value of entropy. On the contrary, a low entropy characteristic of a specific anomaly refers to a concentrated and predictable energy pattern.

For the next stage with regard to classification, the two features (H,CVH,CV) are so minute yet so useful in making up a feature vector.

C. Distress Classification using Machine Learning

Three types of road pavement conditions are distinguished by the authors:

1) Class 1 (Short-time distress): Damages like potholes and manhole covers that only affect a few square meters.
2) Class 2 (Long-term distress): Wear and tear cracking and rutting are examples of damages resulting from an area of several m2.
3) Class 3 (No-distress): Road segments that don't appear to be damaged.



Three categories of supervised learning algorithms are used in their experiments:

- Decision Trees (DT): Easy-to-understand models that make predictions quickly.
- SVMs, or support vector machines: SVM is renowned for its high accuracy with a limited number of features and searches for the best hyperplane to divide classes.
- The most common class among the k nearest points in the feature space is used by k-Nearest Neighbors (kNN) to identify the object's class.

III.EXPERIMENTAL RESULTS

Real-world data gathered from urban and suburban settings in Florence, Italy, at a steady speed of 30 km/h, was used to validate the system.

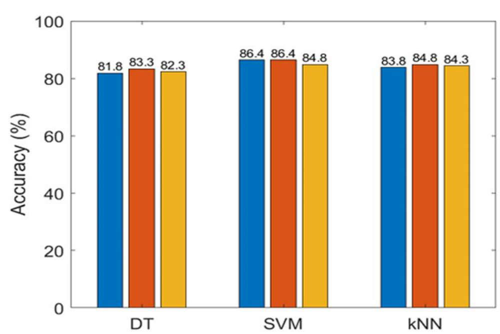
A. Qualitative Time-Frequency Analysis

STFT plots are used to show the many kinds of distress:

1) No-Distress: It shows a consistent energy distribution across frequency and time.
2) Pothole (short-time): Detect the very intense, sharp "blob" that was dispersed across frequencies but highly localized in time.
3) Long-term fatigue cracking was less severe but the change in energy was more persistent over time.
4) Energy change is more persistent over time but less severe, manifested by long-term fatigue cracking.

B. Quantitative Classification Performance

1) Overall Performance: When combining data from both sensor locations, the linear SVM model performed the best, achieving an accuracy of 86.4%. The confusion matrix revealed that the "Long-time distress" class was the hardest to distinguish, most likely due to the fact that it shared more characteristics with the other two classes.
2) Effect of Sensor Location: One of the main findings are the floorboard mounted sensor produced more accurate results. With an accuracy of 91.9%, the Cubic SVM was the best model for this location. For all classes, the confusion matrix showed excellent precision (Short-time: 97%, Long-time: 84%, No-distress: 97%).



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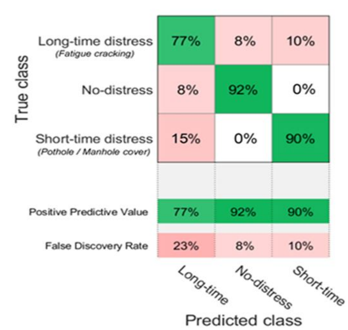

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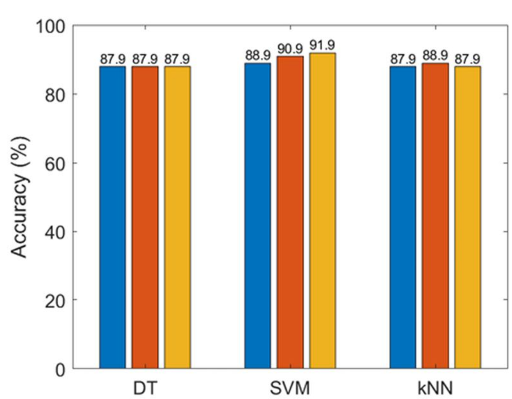

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IV. CONCLUSION

A technological framework solution for automated and economical road surface monitoring has been conceptualized and practically demonstrated by Martinelli et al. in the reviewed work. The suggested system can identify different kinds of road surface distress with a very high degree of precision by cleverly combining time-frequency signal processing (STFT) with robust machine learning classifiers (SVM) and clever feature extraction (CV and Entropy). According to one of the results, performance improvement is significantly influenced by the sensor location (floorboard).

The study is an effective attempt to balance the need for more affordable, readily deployable solutions with the issue of expensive monitoring systems. It establishes a strong foundation for the upcoming development of extensive mobile crowd sensing platforms, which have the potential to completely transform how local governments manage and protect their priceless road infrastructure. The authors employed the right methods, the results are convincing, and there is a good probability that they will be used in the real world. This is a big step forward in the disciplines of smart infrastructure and sensor-based analytics.

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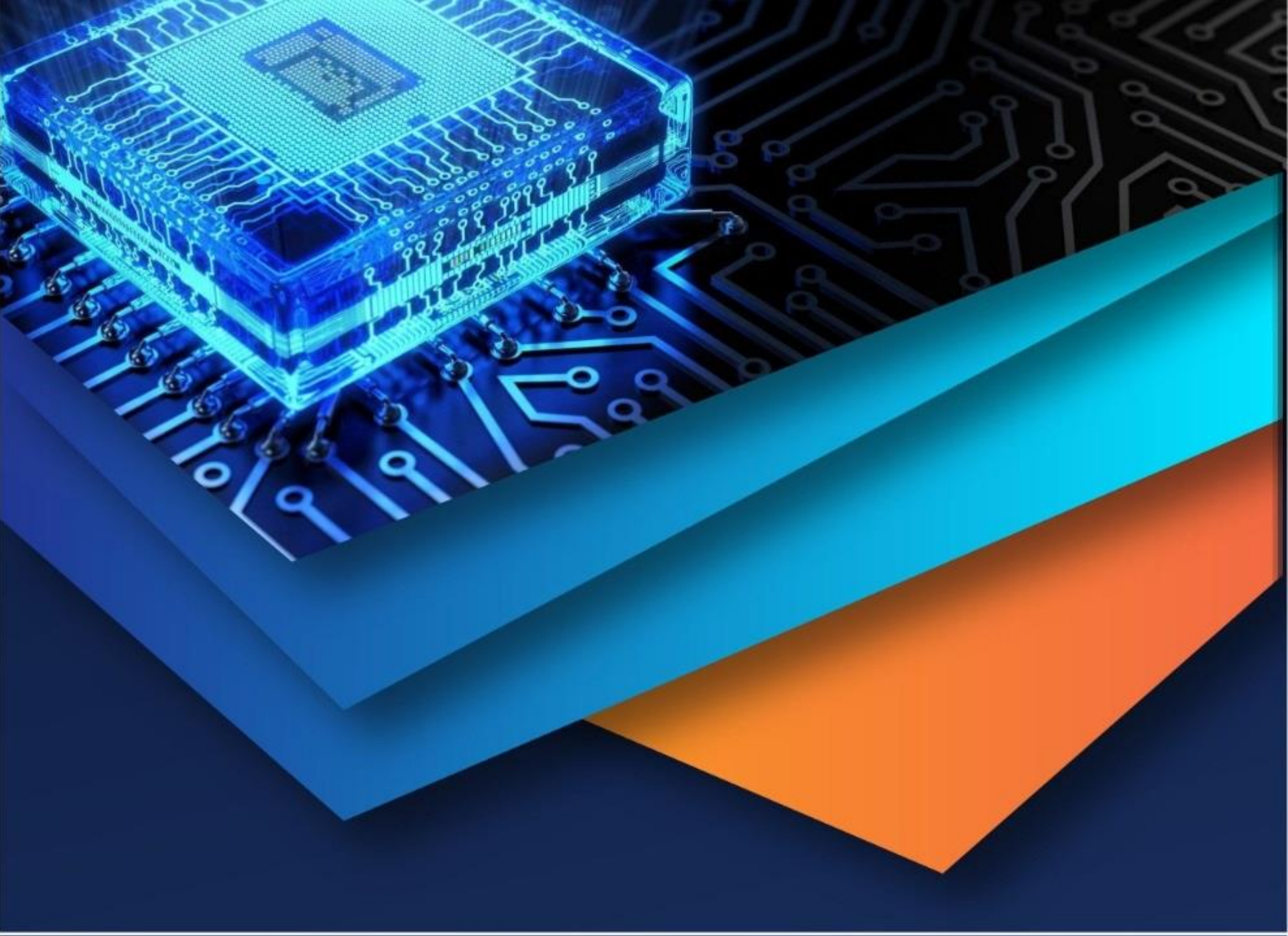

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