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Optimizing UAV-Based Pavement and Roadway Assessment Techniques for Enhancing Rural Infrastructure Resilience in the United States

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Abstract- In this research, UAVs, GNSS, GIS, and machine learning are studied to enhance rural infrastructure resilience and better the assessment of the pavement condition. High-resolution UAVs can offer an effective way of gathering rich data about road-related situations in isolated places and distant highways. GNSS guarantees a high degree of accuracy in locating points, whereas GIS provides out the capability of analyzing space and mapping a network of roads. They trained machine-learned models (a Random Forest classifier) to forecast maintenance requirements on the basis of such factors as the Pavement Condition Index (PCI), traffic volume (AADT), and environmental elements, such as rainfall and rutting. The model had an almost perfect accuracy, precision and recall indicating that it is effective in determining road segments which need to be maintained. This system provides a resource allocation approach based on data-driven proactive maintenance, to enhance the decision-making process. Some improvements in the system in the future may involve adding real-time traffic data, weather prediction, and high-technology UAV systems to manage rural infrastructure to a better extent.

I. INTRODUCTION

The resilience of infrastructure in the rural community is critical in providing safety, accessibility, and economic stability to the community. Geographic seclusion, lack of resources, and the severity of the environment are some of the challenges that are likely to be faced in rural areas (Yohanes et al., 2025). It is even harder to maintain infrastructure, particularly roadways, in such regions, as roads are getting worse, access to repair and maintenance materials is limited, and the staff is insufficient to implement prompt measures to rescue situations. Therefore, the resilience of these infrastructures, which can be described as their capability to endure and revert to their states following the damages, is significant in determining the sustainability of the rural communities in the long run.

Resource scarcity in terms of financial investment and skilled manpower is one of the main challenges of rural infrastructure maintenance. The rural regions tend to be equipped with the old infrastructure monitoring techniques that are expensive, time-consuming and subject to error (Yu et al., 2024). Moreover, the external conditions (e.g., unusual weather patterns, excessive precipitations, or floods) may increase the worsening of roadways, and regular and precise evaluations are absolutely necessary.

UAVs (Unmanned Aerial Vehicles), GNSS (Global Navigation Satellite Systems), and GIS (Geographic Information Systems) are modern technologies that can solve these challenges. UAVs present an effective and low-cost method of capturing high-resolution images to monitor the pavement conditions in remote locations. Combined with GNSS to provide accurate location information and GIS to analyze, map the anticipated spatial data, such technologies can be used to conduct a faster and more precise evaluation of road conditions to enable quicker decisions and address the need of timely maintenance activities (Vangu et al., 2025). With such advanced technologies in place, infrastructure resiliency in rural locations can be achieved on a larger scale,

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which will benefit rural communities with safer and more sustainable roads.

Objectives

1. To Conduct Exploratory Data Analysis (EDA) for Pavement Condition Assessment.
2. To Develop and Evaluate a Machine Learning Model for Maintenance Prediction.

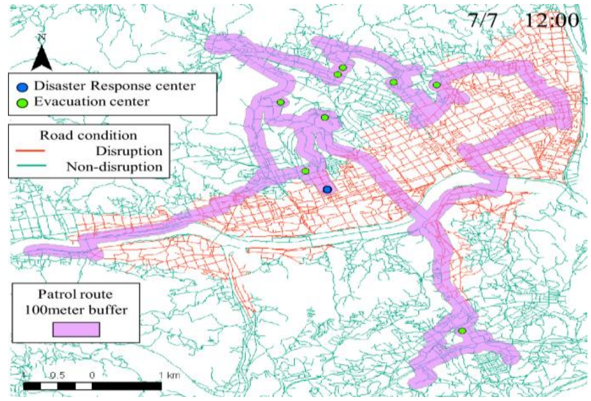
To Visualize Key Insights for Pavement Condition and Maintenance Prediction.

II. LITERATURE REVIEW

UAV-based Pavement Assessment

Infrastructure monitoring using Unmanned Aerial Vehicles (UAVs) has received a lot of interest in the recent past. The UAVs have cameras with high-resolution, LiDAR sensors, and other control technologies that enable them to inspect and survey the pavements and roadways in detail and in a brief time (Ianca et al., 2024). Channeling of previous literature has demonstrated the cost-efficiency and effectiveness of UAVs in comparison to manual surveys or vehicle-mounted systems in general. UAVs will also give an aerial perspective of the vast covered regions thus making it easy to determine the road conditions without necessarily having human personnel at the field.

The capability of UAVs to come to areas that are difficult to reach or dangerous is one of the advantages of UAVs. As an example, UAVs may be used in rural areas to survey roads inaccessible because of the geographic or environmental circumstances of remote mountain roads or post-flood areas (Outay et al., 2020). Moreover, UAVs are able to record pictures and videos far more frequently and with higher quality, and it is possible to detect cracks, potholes, and other defects on the surfaces better. This said, UAVs are not without limitations. Bad weather, including high winds, rain or fog might affect their functionality and restrict their application. Also, the price of advanced sensors on the UAVs might remain prohibitive to certain areas, especially in the economically underprivileged areas.



Source: (A Map Showing How UAVs Can Be Deployed across Various Road Segments for Condition Monitoring, Highlighting Difficult-To-Access Areas)

GNSS and GIS in Roadway Assessment

The use of GNSS (Global Navigation Satellite Systems) and GIS (Geographic Information Systems) in roadway evaluations are important. GNSS is also available and gives engineers very precise location information, which enables them to map and monitor the condition of roads (Upadhyaya et al., 2024). This technology is especially desirable when it comes to ensuring that the road segments under inspection are properly located that would prove essential in long-term tracking and maintaining scheduling.

Spatial data are visualized and analyzed with the help of GIS. Using GNSS location data incorporated into GIS mapping systems, it is possible to develop maps and model of roadways in detail. With GIS, one can identify the regions where there should be certain deterioration, e.g, zones with high traffic or inadequate drainage, and conduct the prioritization of the maintenance work (Toma et al., 2021). Moreover, GIS based systems allow introduction of environmental data like rain distribution, which could be forecasted to determine wear and tear of pavement with a period of time. Combined, GNSS and GIS allow providing a better multi-dimensional and moving approach to infrastructure management. Such technologies can facilitate, besides the evaluation of the conditions on the roads, the long-term strategies and choices that are needed to ensure successful infrastructure resilience.

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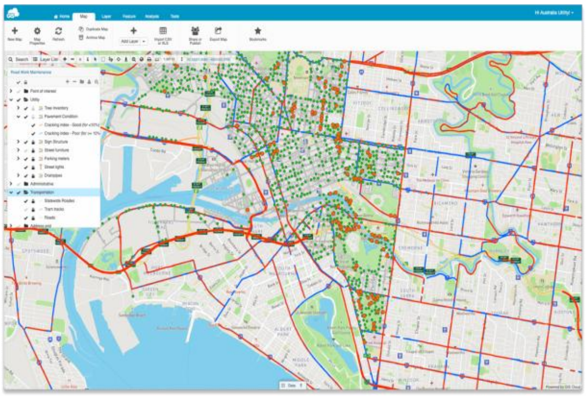


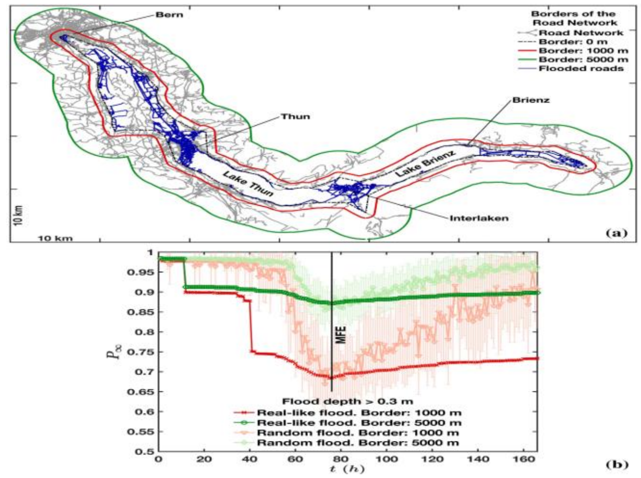
Source: (A Map Showing GNSS Data Points on a Road Network, with GIS Overlays Highlighting Different Pavement Conditions)

Current Challenges in Rural Infrastructure

The maintenance and monitoring of rural infrastructure pose a special challenge since it is not an easy task. Most of the rural communities have few populations that may cause shortages in funding and human resources to maintain the infrastructure (Michael, 2025). Moreover, the rural roads are not regularly maintained, and in many instances, investments are done inadequately, thus they deteriorate faster. These problems are further worsened by the absence of viable solutions that are based on data.

Regular inspection proves to be one of the major problems when it comes to the maintenance of infrastructure in rural areas. Unreachable locations might not possess the infrastructure needed to enable frequent and detailed inspections (Owen and Michael, 2025). Moreover, there is the impact of environmental conditions like harsh weather conditions, heavy rains or floods which can lead to a quick deterioration in pavement and thus the situation needs conventional intervention which cannot be met by the traditional ways.

In order to deal with these issues, there is an increasing demand of effective, data-driven methods that would be capable of forecasting the needs of maintenance. CNSS, GIS, and the application of UAVs can be combined to present a viable answer to this situation and offer real-time physical data acquisition opportunities, enhanced choice-making process, and focused maintenance approach methods (Quamar et al., 2023). Through such technologies, rural infrastructure management will be able to shift to a more active and sustainable paradigm that will be resilient and have greater performance in the long run.



Source: (A Map Highlighting Rural Areas with Infrastructure Issues such as Flood-Prone Zones)

III. METHODOLOGY

The data utilized in the given research is offered by secondary data on Kaggle, which contains such factors as pavement condition, traffic volume, and environmental factors that are important in evaluating the necessity of road maintenance (Gifrey, 2025). The pavement condition is measured using the Pavement condition Index (PCI) that aid in the assessment of deterioration level. The measurement of traffic is through Annual Average Daily Traffic (AADT), which gives the information of the utilization of a road as well as the stress that it is likely to experience. Environmental variables, including general rainfall, and rutting, are taken into consideration to assess the effects of weather circumstances on the deterioration of pavements (Gifrey, 2025). Questionable information cannot be overestimated because valid and quality information is the primary element in creating working prediction models. Efficient data will make it possible to create better machine learning models capable of forecasting the maintenance demands in rural neighborhoods by means of more accurate knowledge about the factors affecting the road conditions and demanding routine maintenance.

In making sure that the data is ready to be consumed to create machine learning models, several preprocessing steps are undertaken. This involves data cleaning of missing data or irrelevant data, the encoding of categorical data like road type and asphalt type into numerical format, and standardization of the ranges of continuous variables like PCI and AADT (Peace et al., 2024). The feature scaling is to make sure that none of the variables is disproportionately affecting the model because of its large magnitude.

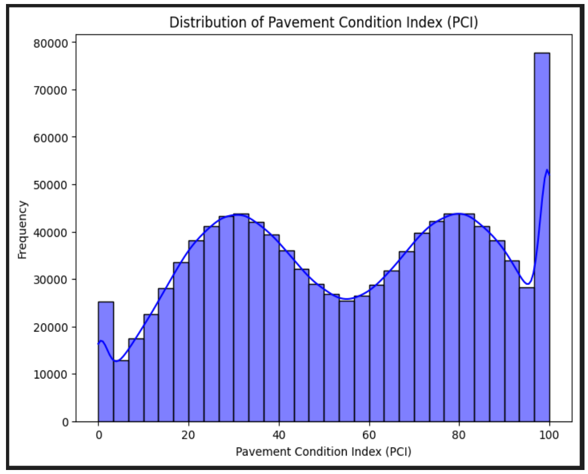
The key component of this process is featuring engineering during which features of the model are added to increase its predictive ability (Heaton, 2016). As one example, the last remaining time was the time since the last maintenance, which is computed to determine the effect of recent maintenance to the present state of the situation. Other derived characteristics are the average rainfall which may give an insight on how weather patterns influence the degradation of the pavement.

Random Forest is preferred when selecting a model because of its strength and capacity to deal with non-linear and multifaceted connections between variables (Roy and Larocque, 2022). This model fits the binary classification issue of determining whether there should be maintenance on a road segment (1) or not (0). Key measures of performance that the model uses to ascertain its performance are accuracy, precision, and recall, and ROC-AUC, which are used in order to ensure that the model would make reliable predictions. Such measures will aid in determining the overall functionality of the model in determining the right road segments to be maintained.

IV. RESULTS AND DISCUSSION

Exploratory Data Analysis (EDA) for Pavement Condition Assessment

Figure 1: Distribution of Pavement Condition Index (PCI).



To perform Exploratory Data Analysis (EDA) to determine the pavement condition, one of the major visualizations will be the distribution of the Pavement Condition Index (PCI), which determines the state of the road surface. Figure 1 displays the values distribution of PCI demonstrating that there are some significant patterns. The histogram and overlaid kernel density estimate (KDE) indicates that, the PCI values are fairly distributed, that is there are specific commonly distributed intervals. The maximum reading is observed in a high location of the PCI scale implying that a large number of road sections are of good pavement conditions (PCI is near to 100). Nevertheless, one can also find substantial amounts of segments having lower PCI values (between 0 and 40), which evidences the fact that the pavement has deteriorated in certain places significantly.

Machine Learning Model for Maintenance Prediction

Table 1: Classification Report and Confusion Matrix for the Random Forest Model.

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	104418
1	1.00	1.00	1.00	105297
Accuracy			1.00	209715
Macro avg	1.00	1.00	1.00	209715
Weighted avg	1.00	1.00	1.00	209715

Random Forest Classifier was employed to develop and test the machine learning model predicting the road maintenance needs. Some of the most important

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measures that were used to assess the performance of the model are accuracy, precision, recall, and F1-score. As illustrated in Table 1, the model has a high accuracy of 0.9999 and this could be taken as a clear indication of an extraordinary capacity to classify roadness correctly.

The model had scored 1.00 (0 no maintenance needed and 1 maintenance required) in both classes in terms of precision, recall, and F1-score. This implies that the model was capable of identifying the two categories correctly with no false positives or false negatives. The mean support of the two classes (104,418 with the support of no maintenance needed and 105,297 with the support of maintenance needed) indicates the prevalence of the road parts in the data.

This is because the model has high performance due to the capability of Pavement Condition Index (PCI), traffic volume (AADT), and environmental factors are complex variables learned by the model. The features contribute to proper predictability of maintenance of road segment.

Table 2: Confusion Matrix

	Predicted: 0	Predicted: 1
Actual: 0	104416	2
Actual: 1	0	105296

The confusion matrix also supports the performance of the model demonstrating no misclassifications. All 104416 cases of no maintenance were accurately categorized as 0 and all 105296 cases of maintenance required were accurately categorized as 1. This ideal division denotes that the Random Forest model was most effective in this binary classification tool.

Key Insights for Pavement Condition and Maintenance Prediction

Figure 2: Distribution of Road Maintenance Needs.

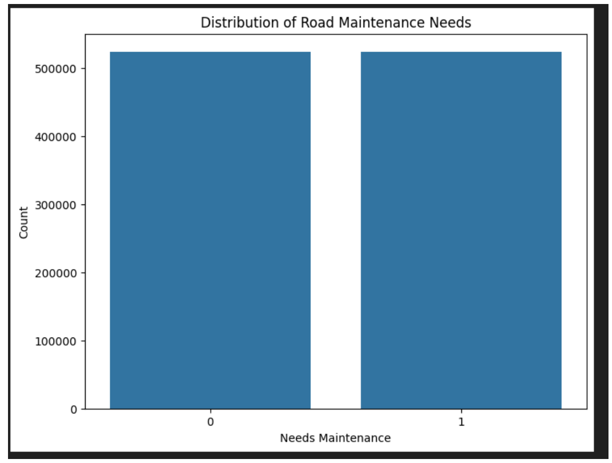
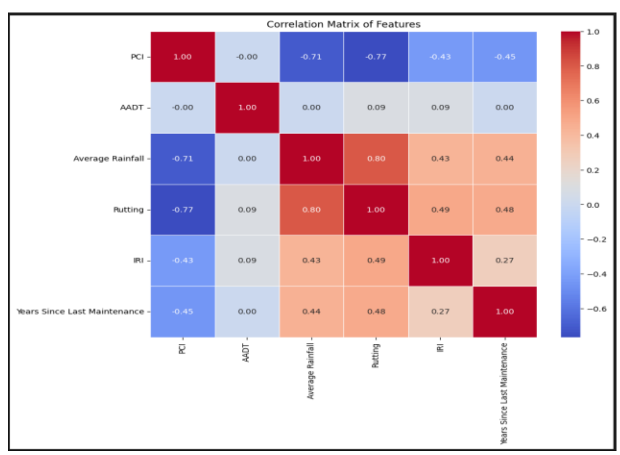


Figure 2 illustrates the distribution of the road maintenance requirements within the dataset and the categories indicate what roads segments should be maintained (1) or otherwise (0). According to the histogram, there is an equal distribution of the two classes with almost equal amounts as the two groups of maintenance needed and no maintenance needed. To be more precise, the number of road segments belonging to each of them exceeds 500 thousand, which shows that the data is balanced between the two categories, which is the best way to train machine learning models without worrying about the class imbalance issue. This even distribution of data is important because it allows the model to have adequate data of each of the classes to learn and it is simpler to judge the performance of the model without favoring one type of classification.

Figure 3: Correlation Matrix of Features.



The correlation matrix of the figure 3 gives clues on the relationships existing among the key features affecting the road maintenance needs. There is a significant correlation between Pavement Condition Index (pci) and the Average Rainfall (r = -0.71), which is negative meaning that the higher the rainfall, the lower is the pavement condition. Also, Rutting and Average Rainfall are strongly positively correlated (r = 0.80) implying that the higher the amount of rainfall, the more the rutting on the roads will be experienced.

The second significant observation is the negative correlation of PCI and Rutting (r = -0.77), that indicates the existence of poor pavement conditions and severe rutting are correlated. Years Since Last Maintenance has moderate positive relationships with both Rutting (r = 0.48) and also IRI (r = 0.44), meaning that roads that are older in terms of not being maintained are more prone to be worse in rutting and roughness. The relationships indicate that environmental and maintenance factors play a great role in determining the road condition, implying the significance of taking such attributes into account when predicting road maintenance.

Figure 4: PCI vs. AADT with Maintenance Need.

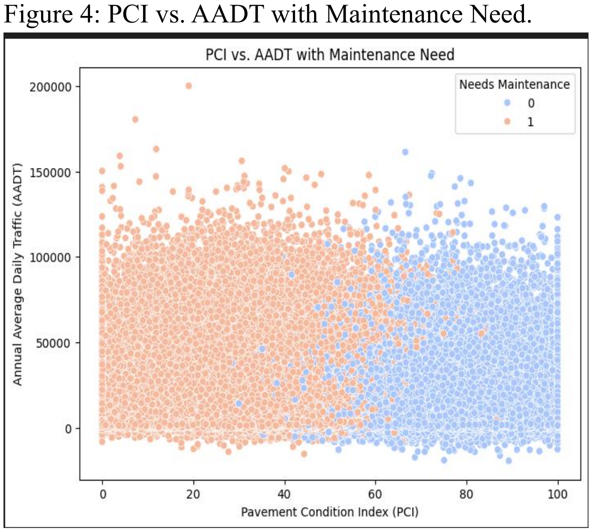


Figure 4 is the scatter plot that shows the dependence between Pavement Condition Index (PCI) and Annual Average Daily Traffic (AADT), with the blue color representing the segments of the road that require no maintenance and the orange representing the ones that need maintenance. It is also observable that the plot exhibits a clear tendency that the more segments have a better PCI value (i.e., the better the road conditions), the more likely it is that they were considered as requiring no maintenance (blue points), whereas the less significant a segment is characterized by its PCI value (i.e., the poorer the road conditions), the more likely it has to need maintenance (orange points).

Moreover, AADT is broadly distributed in both categories of maintenance, and it can be assumed that the volume of traffic is not always equal to the necessity to maintain it in the given dataset. The two groups contain road segments with heavy traffic (more than 100,000 vehicles), suggesting that other factors (environmental conditions, previous maintenance, etc.) can be of more significance to determining the need of maintenance compared to traffic.

Figure 5: PCI vs. Average Rainfall with Maintenance Need.

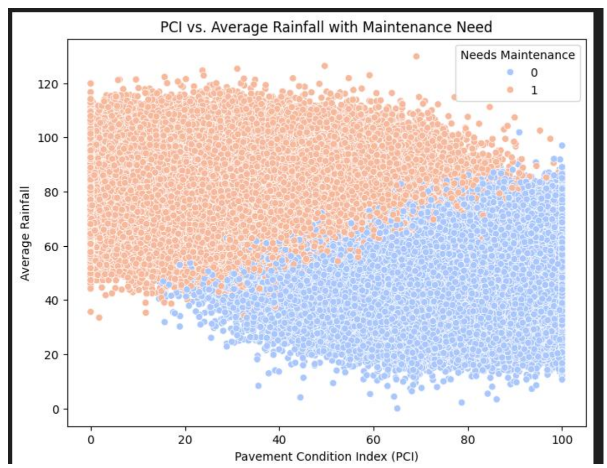


Figure 5 provides a scatter plot that shows dependence between Pavement Condition Index (PCI) and Avenue Rainfall with road segments being divided according to the maintenance requirements (blue as no need of maintenance and orange as required maintenance). The plot shows that the proportion of road segments with a higher PCI value, thus is in a better condition due to pavements is also more likely to require no maintenance (blue points). Conversely, road sections that have smaller PCI values, which are of poor pavement conditions, are likely to be in maintenance (orange points).

Also, plot indicates a definite negative correlation between PCI and Average Rainfall- pacifing areas have lower pavement conditions. This implies that the areas that receive more rainfall may have greater degradation of their roads as a result of degradation by water and therefore be facing more maintenance needs.

Figure 6: Rutting vs. Needs Maintenance.

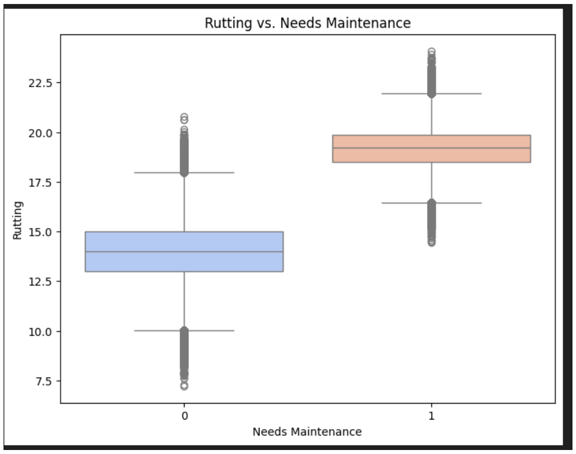


Figure 6 contains the boxplot of the relationship among Rutting and the necessity of maintenance. The plot shows that the road segments that need maintenance (orange points) typically have larger rutting values and the median rutting level is 20. The opposite scenario is that the median rutting of road segments with no maintenance needs (blue points) is lower than that of those with maintenance needs (15). This implies that the more a rutting is high the more the rutting would demand proper maintenance because rutting can seriously compromise the structural stability of the road.

Also, the boxplot indicates existence of outliers in both categories. The outliers in the segments requiring maintenance are more significant, this is an indication of extreme rutting in these areas, which also serves to justify the necessity to consider serious pavement conditions. These results imply that rutting is an essential element in the determination of maintenance requirements, and this matter should be considered during the decision-making process.

V. PRACTICAL IMPLICATIONS

The suggested system combining UAVs, GNSS, GIS, and machine learning to determine the pavement conditions has a high potential to improve the resiliency of rural infrastructure. With the use of UAVs when fitted with cameras and sensors with high resolutions, the system is capable of providing a fast and precise estimation of the state of roadways in rural settings that are not easily accessible. These three data, along with GNSS when tracking exact location and GIS when analysis of space, make it possible to make the mapping and identification of road segments, which need maintenance, efficient. Machine learning models have the ability to offer proactive interventions, not reactive intervention, as it is based on historical and environmental data to predict future requirements of maintenance.

This system can be presented in phases in rural infrastructure resilience projects. First, UAVs and sensors would be introduced to get the background information on the pavement conditions. Then, the data would be assigned to the machine learning models that will predict the areas that could undergo deterioration. In the long run, the system would be advanced to incorporate real time monitoring and forecasting maintenance to be maintained which would enable the rural communities to distribute resources more efficiently and to save on money used to repair the roads.

VI. LIMITATIONS

Irrespective of its likely potentials, there are multiple limitations of the proposed system. First, UAVs can only be used in favorable weather conditions since strong winds, rain and even fogs can disrupt the UAV activities. Moreover, UAVs can be very useful in the assessment of the conditions of the road and insufficient in the analysis of the stability of the roads under the surface.

The second weakness is the expensive initial expense of adopting UAV-based system of monitoring, which would be a behemoth to low-budget rural regions. The technology, such as drones, data analysis software, and sensors need might be a major investment to cover the financial costs. Moreover, the machine learning models rely on the quality and quantity of data present. In parts of rural areas, the amount of history may not be available to train accurate models and hence limit the predictive capabilities of the system. Finally, the success of this system may be restrained by the unavailability of qualified experts to read and respond to the information, and good preparation and inclusion of local capacity in the implementation should be crucial to success.

VII. CONCLUSIONS

The present work demonstrates the important role of UAVs and machine learning in enhancing pavement condition monitoring, especially the stability of rural infrastructure. UAVs offer a cost-effective way of gathering the high-resolution data of the road conditions, particularly in remote location where conventional inspection technique methods may present a problem. In combination with GNSS to determine the location with high precision and GIS to map the area, the technologies allow making the road networks evaluation accurate and timely. This process is further compounded by integrating machine learning models to anticipate the maintenance requirements according to previous and environmental trends, enabling to plan a rather than react to the maintenance process.

The model that performed best was the Random Forest classifier with almost perfect accuracy, precision, and recall. The success of the model can be explained by the successful utilization of such features as Pavement Condition Index (PCI), road traffic (AADT), and such environmental variables as average rainfall and rutting. According to the model insights, the features can be extremely important when it comes to predicting accurately the necessary road segments that require maintenance.

In prospect there are a few fields of future work. By including other sources of data like new traffic data, weather data, and sensor real time monitoring of the road conditions a lot of predictive accuracy and timeliness would be added to the system. The UAV technology and machine learning algorithms can continue to be advanced; therefore, the system could be more resource-optimal to more various rural environments.

REFERENCES

[1] Gifrey Sulay. (2025). Pavement Dataset. Kaggle.com. https://www.kaggle.com/datasets/gifreysulay/pavement-dataset.

[2] Heaton, J. (2016, March 1). An empirical analysis of feature engineering for predictive modeling. IEEE Xplore. https://doi.org/10.1109/SECON.2016.7506650

[3] Ianca Feitosa, Santos, B., & Almeida, P. G. (2024). Pavement Inspection in Transport Infrastructures Using Unmanned Aerial Vehicles (UAVs). Sustainability, 16(5), 2207–2207. https://doi.org/10.3390/su16052207

[4] Michael, I. (2025, June 10). Infrastructure Barriers in Remote Rural Areas. https://www.researchgate.net/publication/392557813_Infrastructure_Barriers_in_Remote_Rural_Areas

[5] Outay, F., Mengash, H. A., & Adnan, M. (2020). Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges. Transportation Research Part A: Policy and Practice, 141, 116–129. https://doi.org/10.1016/j.tra.2020.09.018

[6] Owen, J., & Michael, I. (2025, June 5). Broadband and Climate Resilience in Rural Infrastructure. ResearchGate; unknown. https://www.researchgate.net/publication/392663733_Broadband_and_Climate_Resilience_in_Rural_Infrastructure

[7] Peace, P., Chris, J., & victor, L. (2024, November 11). Data Preprocessing for AI Models. ResearchGate. https://www.researchgate.net/publication/385707249_Data_Preprocessing_for_AI_Models

[8] Quamar, M. M., Al-Ramadan, B., Khan, K., Shafiullah, M., & Ferik, S. E. (2023). Advancements and Applications of Drone-Integrated Geographic Information System

Technology—A Review. Remote Sensing, 15(5039), 5039. https://doi.org/10.3390/rs15205039

[9] Roy, M.-H., & Larocque, D. (2022). Robustness of random forests for regression. Journal of Nonparametric Statistics, 24(4), 993–1006. https://doi.org/10.1080/10485252.2012.715161

[10] Toma, M. G., Ungureanu, R. D., & M Dicu. (2021). GIS, a tool for improving the road network management. IOP Conference Series Earth and Environmental Science, 664(1), 012103. https://doi.org/10.1088/1755-1315/664/1/012103

[11] Upadhyaya, S., Prabin Gyawali, Shrestha, S., Bhandari, S., & KC, S. (2024). The Fundamental Role of GNSS in Modern Surveying and Mapping to Support Climate Responsive Land Governance and to Enhance Disaster Resilience. FIG Regional Conference 2024. https://www.researchgate.net/publication/386053006_The_Fundamental_Role_of_GNSS_in_Modern_Surveying_and_Mapping_to_Support_Climate_Responsive_Land_Governance_and_to_Enhance_Disaster_Resilience

[12] Vangu, M. Miluț, & A.C. Croitoru. (2025). Use of Modern Technologies Such as UAV, Photogrammetry, 3D Modeling, and GIS for Urban Planning. Journal of Applied Engineering Sciences, 15(1), 165–174. https://doi.org/10.2478/jaes-2025-0020

[13] Yohanes Kamakaula, Komang Ariyanto, Roys Qaribilla, & Ratnawati Yuni Suryandari. (2025). A Review of the Resilience of Rural Communities in the Face of Climate Change. Journal of Innovative and Creativity (Joecy), 5(2), 22979–22992. https://doi.org/10.31004/joecy.v5i2.3332

[14] Yu, Y., Appiah, D., Zulu, B., & Adu-Poku, K. A. (2024). Integrating Rural Development, Education, and Management: Challenges and Strategies. Sustainability, 16(15), 6474–6474. https://doi.org/10.3390/su16156474