WGEF: An Optimized Deep Learning Model for Recognition of Road Surface Condition Using SVM Classifier

Ramya K. Rajavolu * and Nutakki Jyothi

Department of EECE, GITAM (Deemed to be University), Visakhapatnam, India
Email: ramyakrishnarajavolu9@gmail.com (R.K.R.); jnutakki@gitam.edu (N.J.)
*Corresponding author

***Abstract*—Road Surface Conditions (RSC) play a critical role in daily transportation and infrastructure reliability. Due to heavy public, governmental, and industrial dependence on road networks, maintaining road quality is essential. However, varying weather conditions often lead to road damage, complicating the task of accurately identifying RSC. To address this challenge, we propose a hybrid model combining Deep Learning (DL), Optimization, and Machine Learning (ML) techniques for effective recognition and classification of RSC. The model is developed using a publicly available dataset of road surface images. Preprocessing is performed using Wavelet Transform (W), followed by the extraction of texture features using Gray Level Co-occurrence Matrix (G). Deep feature extraction is conducted using the Efficient-Net (E) model. The resulting features are then optimized using the Firefly Optimization (F) algorithm. Finally, classification is carried out using a Support Vector Machine (SVM). This approach enables accurate RSC identification with a minimal number of data points while maintaining high performance. The combined DL-ML framework demonstrates superior results in terms of key evaluation metrics such as sensitivity, specificity, precision, and accuracy. The proposed model achieves an accuracy rate of 99.38%, specificity 99.3%, sensitivity 99.4% and precision 99.36% respectively. The PBIAS obtained using proposed model is 0.0687%.**

***Keywords*—road surface condition, Wavelet Transform (W), Efficient-Net, firefly optimization, Support Vector Machine (SVM)**

I. Introduction

The goal of this research project is to address surface issues on our roadways, a persistent and usually ignored issue. Road maintenance is necessary in a society that is becoming more interconnected and where quick and secure travel is essential. The irregular conditions of road are a regular irritation that can pose a major threat to road safety and in maintenance of vehicles. Organisations which perform management of road struggle to maintain the current road networks in excellent operating condition due to a lack of funding and pavement repair techniques. Bhatt *et al*. [1] developed a low-cost smart road health monitoring system that identifies the road segment that needs maintenance using smartphone sensors and camera-based monitoring.

Regular monitoring of road infrastructure is also essential to maintain the quality of roads. Tilon *et al*. [2] suggested a cutting-edge Unnamed Aerial Vehicles (UAV)-agnostic system that can perform several real-time, concurrent road infrastructure monitoring jobs. This improves the close monitoring of roads and improve latency in making road surface modified. Weather, heavy traffic, weights, and the age of the infrastructure are some of the factors that cause road surfaces to deteriorate. These sources of deterioration create abnormalities that may endanger pedestrians and drivers, and fixing the abnormalities can be expensive. The creation of systems that automatically identify and categorise road irregularities has been spurred by these limitations. Martinez-Ríos *et al*. [3] discussed detection and classification based on vibration-based techniques.

Image processing models and sensors like ultrasonic are effectively utilized for monitoring of road surface. Sharma *et al*. [4] suggested an effective system which utilizes ultrasonic sensors and Global Positioning System (GPS) model for detecting the condition of road surface. Alrajhi *et al*. [5] discussed the utilization of multiple sensors and IoT technologies. In this many of the relevant Machine Learning Models (MLM) are studied which are helpful in automatic road defect identification. The quantitative and qualitative analysis of the roads can be provided by the Internet of Things (IoT) and sensor technologies. In MLM to more accurately perform the detection of Road Surface Condition (RSC), a multiclass supervised Machine Learning (ML) techniques discussed and utilized GPS data from smartphone to collect the road images [6]. Rao *et al*. [7] discussed the comparative analysis of machine learning model.

An automatic identification and classification of RSC is performed using Convolutional Neural Networks (CNNs) [8]. The accuracy in detection of RSC is

Manuscript received April 3, 2025; revised April 16, 2025; accepted June 3, 2025; published August 7, 2025.

evaluated and achieved a training accuracy of 88%. The involvement of Deep Learning Models (DLM) gaining more significance in problem solving of wider applications. The ML models shown impact on the desired applications. Deep learning approach is suggested for early identification of road surface conditions like dry, potholes, yellow lines etc utilizing UAV [9]. The parameters like F1-Score, accuracy, sensitivity are evaluated. To improve the accuracy, a segmentation based deep learning approach is discussed [10]. The metrics like mean average precision, detection accuracy and detection speed are evaluated.

The detection of RSC or defects in roads is becoming on the significant concern and creating a scope of research which creates impact on various applications. To address the above problems and an automatic detection of road surface depending on the weather condition is designed utilizing the artificial intelligence. This research provides a computer vision-based technologies in addressing the problem. The information provided can effectively utilized for autonomous driving system implementation so that there is a vast increase in road safety, smooth traffic management by diversions. The main objective of this study is to develop an effective and accurate system for the identification and classification of RSC using a novel hybrid approach that combines deep learning, optimization, and machine learning techniques. While previous studies have explored individual deep learning or machine learning models, this work introduces a unique integration of multiple methods to enhance performance.

Specifically, the key objectives and novel contributions of this study are as follows:

- To utilize a combination of Wavelet Transform and Gray Level Co-occurrence Matrix (GLCM) for robust feature extraction from road surface images.
- To leverage the powerful Efficient-Net deep learning model for extracting high-level features, improving recognition capability.
- To introduce a novel optimization step using the Firefly Algorithm for feature selection and dimensionality reduction, ensuring efficient computation and improved accuracy.
- To employ a Support Vector Machine (SVM) classifier on the optimized feature set for precise classification of road surface conditions.
- To design and propose the Wavelet, GLCM, Efficient-Net, Firefly optimized (WGEF) SVM model, which is the first of its kind in combining these techniques for RSC identification.
- To evaluate the model using the publicly available T. Zhao dataset and demonstrate superior performance with an achieved classification accuracy of 99.36%, outperforming existing methods.
- To analyze training behavior, loss trends, and generalization capability through confusion matrix evaluation, and propose future improvements in recognition time and real-time deployment.

The novelty of this work lies in the integration of multi-stage feature extraction (Wavelet + GLCM + deep features) with bio-inspired optimization (Firefly Algorithm) and a machine learning classifier (SVM), forming a hybrid model that achieves high accuracy with reduced computational cost. The Firefly Algorithm reduced the dimensionality of the extracted features by approximately 30%, significantly lowering the computational burden without sacrificing accuracy. This addition helps to quantify the claimed reduction in computational costs. This combination has not been previously applied to the road surface condition identification problem, making this approach both original and effective. The further discussion of paper is organised to discuss the existing ways in identifying the RSC in Section II. The designed model for identification of RSC is discussed in Section III. In Section IV the examining of suggested model is performed and the results are shown. Finally, Section V concludes by presenting the key finding, overall summary of work and limitation of work.

II. Related Work

Many deep learning techniques were introduced in the field of road surface condition identification. This section discusses the approach towards detection of RSC by various researchers. Abdic *et al.* [11] suggested a DL model i.e., Recurrent Neural Network (RNN) architecture for identification of wetness on the road surface utilizing audio bins which are obtained by the interaction of road and tyre. Training and comparison of two different Deep Convolutional Neural Network (DCNN) models, on their use in road friction estimation and outline the difficulties in building appropriate datasets and training the classifier using the training data that is now accessible [12]. This work is limited to one condition and mainly depending on the travel data of vehicles. The identification depends on the speed of the vehicle travelled.

To overcome the issue, road side camera data is utilized for detection of RSC. The cameras available in road side help in detection some of the road conditions. Integration of road side camera images and weather data achieved from weather information stations for RSC identification [13]. This data shown effective improvement in identifying the condition of road. Efficient deep learning models like DenseNet, NASNet and MobileNet for identification of RSC utilizing camera image and weather data [14]. The integration of weather data and road side camera image improves the RSC over poor visibility conditions. Seo *et al.* [15] suggested a DNN model and LiDAR classification for RSC detection. The method LiDAR utilized gives the data regarding the reflectivity and points on the cloud which depend on the road surface.

They are different type of techniques based on the computer vision and successfully implemented on many of the applications. PGA-Net for surface detection utilizing pyramidal features, global context attention network [16]. The network performs pixel wise detection of the defects on the surface. The mean pixel accuracy is evaluated. Road damage can be automatically identified and classified using Digital Image Processing (DIP) technology. A multiclass SVM is used to automatically classify roads with defects [17]. Road surface damage detection using Deep Learning (DL) has received more attention and improved detection performance in recent decades. Road surface damage detection system uses the quick detection technique YOLOv3, YOLOv4 which is enhanced by Proportional-Integral-Differential (PID) optimisation, YOLOv5, YOLOv5x, YOLOv10 [18–22].

Complete reconstructions and significant structural and financial damage of the infrastructure may result from delayed assessments. Naddaf-Sh *et al*. [23] suggested efficient and scalable DL Approach for Road Damage Detection. The error analysis is evaluated for different type of images. RSC in different countries considered and suggest deep learning model [24]. A large-scale heterogeneous road damage dataset of 26,620 photos taken with smartphones in several nations (including Japan, the Czech Republic, and India) are considered for detection of road damage and classification.

Hegde *et al*. [25] considered big data for detection of road damage. Ensemble learning model is designed for IEEE 2020 global dataset. The F1-Score achieved is 67%. There is further need to improve the F1-Score when considering big data. A multi-national RDD2022 big dataset is considered a deep learning model is designed to detect the road surface condition [26]. The F1-Score achieved is 76.9%. YOLOv7 model designed for RSC detection [27]. The F1-Score evaluated is 81.7%. Wang *et al*. [28] suggested YOLOv8s model for identification of road surface using bigdata. The construction of the designed YOLO model is integrated with BiFPN concept. This process of optimization reduces the load for computation and the size of the model. A CNN-YOLO is designed for identification of RSC and the result evaluated achieved an accuracy of 92% [29]. Some of the hybrid models utilized in detection of road surface is discussed. Hadj-Attou *et al*. [30] utilized CNN-GRU and CNN-LTSM model for detection of road surface condition. Khaled *et al*. [31] proposed KNN-Gaussian model for final lane discovery of degraded road surface.

The limited feature representation in existing models and inconsistent performance across diverse road and weather conditions lead to develop a novel model. To further improve the accuracy rate and reduce the load for computation in this paper a deep learning optimization model is deigned. The design and implementation of proposed work is discussed in Section III.

III. Methodology

The detection of road surface condition is performed using the suggested methodology which includes four stages in implementation. The four stages are preprocessing, feature extraction, feature reduction, classification. The framework of the model is shown in Fig. 1.

A. *Preprocessing*

One of the important steps in digital image processing applications is preprocessing. The dataset is considered in this work for processing our designed model [32]. The dataset images size is 240×360 pixels with 96 dpi and is reduced to a standard size of 224×224×3 pixels. The size of the kernel is 3×3. All the images in the dataset are initially resized to ensure effective training and classification of data. The resized images are converted to grey scale images. The grey scale conversion helps to hype the edges, contrast, texture, and shape of the image while maintaining the colour range. Most of the computer vision models utilize this conversion where colour is not given more importance in further processing. Wavelet Transform is applied to the images. The images get decomposed into different frequency components as shown in Fig. 2. The Wavelet provides both spatial and frequency information which helps in localizing the road surface datapoints. The Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH) details of the input image is extracted in which multi-level datapoints are captured at different scales.

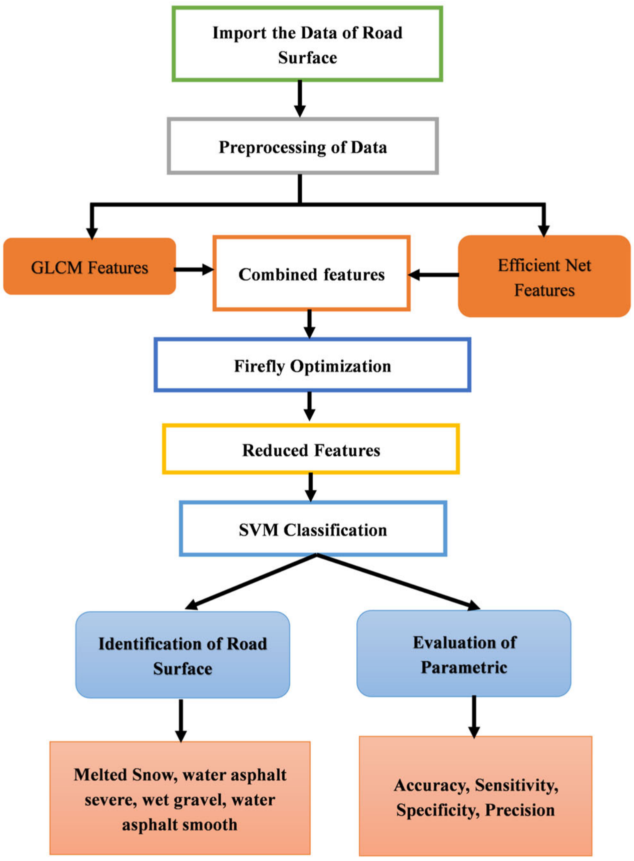

Fig. 1. Framework of suggested methodology.

B. *Feature Extraction*

The datapoints are extracted for the Wavelet Transform (WT) processed images. Compute Grey Level Co-occurrence Matrix (GLCM) for each sub-band LL, LH, HL and HH processed by WT. GLCM is utilized to evaluate the texture datapoints such as contrast, correlation, energy, homogeneity. In this work, the GLCM is computed in different angels such as 0°, 45°, 90°, 135° to evaluate textures in every direction [33]. The other angles are observed but achieved good results in these four angles. Organise GLCM data points from all the sub-bands to form a comprehensive feature of texture. Normalise the retrieved data points to a consistent scale between 0–1 so that each feature contributes equally to the classification process. The GLCM features skewness and kurtosis is evaluated and values shown in Table I.

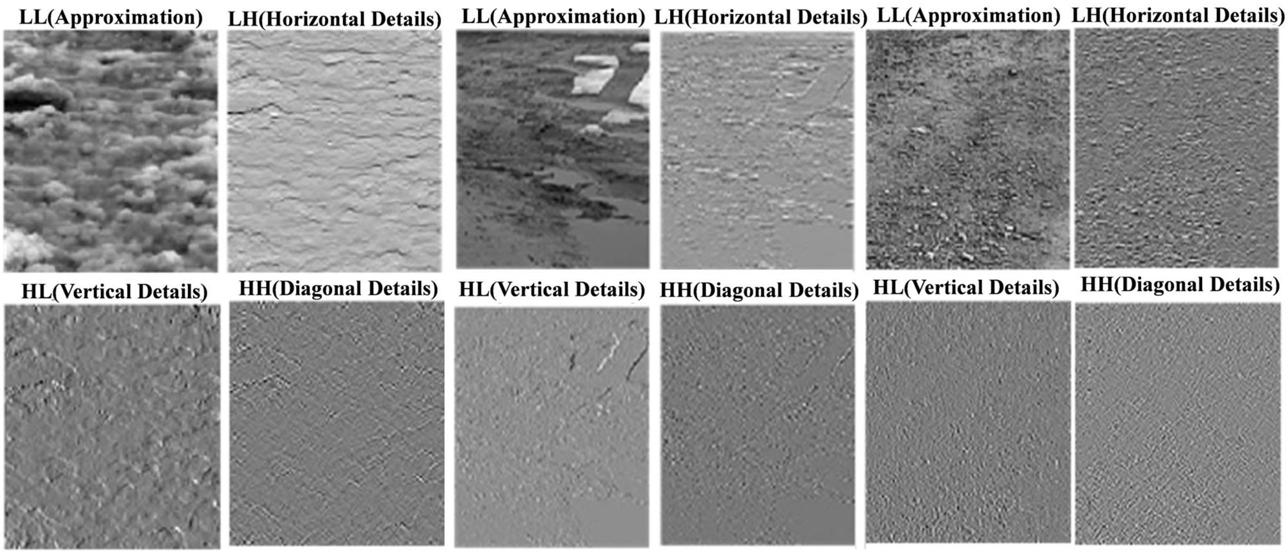

Fig. 2. Wavelet transform process.

TABLE I. SYSTEM SPECS

Image/Parameter	Kurtosis	Skewness
Image 1	3.605	0.14
Image 2	5.76	0.765
Image 3	3.62	-0.313
Image 4	2.22	0.015
Image 5	5.53	-0.847
Image 6	2.67	-0.502

When training a model, a dataset with a high degree of skewness could generate learning bias due to its unequal distribution. Similarly, distributions with heavy tails and maybe outliers are indicated by high kurtosis. These findings highlight the need of feature selection and normalisation before training a model to guarantee consistent learning and better generalisation.

1) Efficient-Net model

For extraction of data points the Efficient-Net model scales the network and makes it effective. Train Efficient-Net on the road surface dataset. Efficient-Net uses a sequence of MBConv blocks to classify road surfaces by initially extracting low-level data points from the input picture, such as edges and textures, and then gradually extracting more complicated characteristics associated with road conditions, such as cracks, potholes, and roughness. Global characteristics gathered from the entire picture using global average pooling are used to make the final judgement. A fully linked layer with SoftMax activation is then used for classification. The step-by-step procedure of the network model is shown in Fig. 3.

2) Input layer

All the images are typically resized to 224×224 pixels. After resize, the images are been normalized by assuring the pixels values between 0 and 1.

3) Stem layer

Efficient-Net's stem layer is a convolutional layer with a large kernel size i.e., 3×3 is utilized that can swiftly identify the data points with highly integrated to road surface conditions based on the edges, and textures in the input picture. A stride 2 is utilized in this layer to reduce the spatial dimension which helps in improving the receptive field. This layer of the architecture is the first to extract low-level characteristics from road surfaces, such as edges and basic forms. After detecting low level, concentrate on condition of the surface.

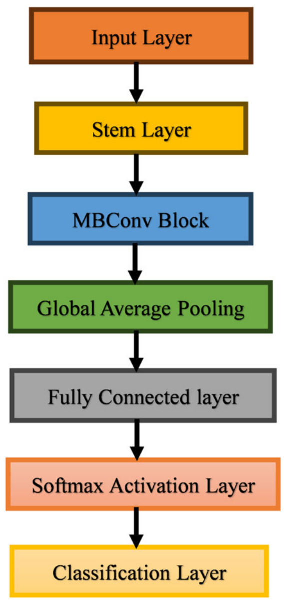

Fig. 3. Process flow of Efficient-Net model.

4) Mobile Bottleneck (MB) convolutional block

In the Efficient-Net this block extract key data points which consists of depth-wise blocks and structures. More number of complex data points are captured with less parameters. Efficient-Net employs computationally efficient depth-wise separable convolutions. Prior to performing a pointwise convolution (1×1 convolution to merge the outputs from depth-wise convolutions), it applies a filter to each input channel in a depth-wise convolution. From the supplied image, these blocks gradually extract increasingly intricate data points. They are low level data points (edges, shapes, textures), high level data points (textures of road surface, cracked patterns, wetness in the surface, potholes, surface covered with mud). The Mobile Bottleneck (MB) block consists of inverted residual structure which allowed the Efficient-Net to extract fine details from the image and keeps the lower range of computational cost. These MB blocks are repeated for number of times in layers to learn significant data points of road surface. In this step, a swish activation function is utilized after performing 1×1 convolution operation and after performing 3×3 depth-wise convolution. The activation function is given as, $swich(x) = x \times \sigma(x)$, where $\sigma(x)$ is the sigmoid function.

5) Global Average Pooling (GAP)

Efficient-Net employs Global Average Pooling (GAP) following several MBConv blocks. The output from the last MBConv block is reduced in spatial dimensions by GAP to a single vector that represents global characteristics. The complete spatial feature map is summarised by the GAP layer, which averages each channel's feature map and condenses each channel's spatial information to a single value. In the context of road surface classification, this phase aids in concentrating on global information, which would assist identify more general characteristics of the road surface, such overall texture, condition (such as smooth vs rough), or the existence of damage.

6) Fully connected (dense) layer

A fully connected (dense) layer receives the GAP output and uses it to translate the global characteristics to the final output class. This would produce a probability distribution across several road classes for road surface categorisation. As the considered dataset in this work consists of 27 subcategories, this layer utilizes 27 units and performs data points extraction that maps the global level data points.

7) SoftMax activation

The fully connected layer is followed by a SoftMax layer. Each class is given a probability via the SoftMax activation, which transforms the fully connected layer's output into a probability distribution. The final classification result will be the class with the highest probability. It designates the most likely road state (smooth, cracked, snow, mud, asphalt, etc.) for road surface categorisation.

8) Classification layer

Lastly, the classification layer calculates the loss which is usually cross-entropy loss for classification tasks and offers the required input to the model during training so that the weights may be adjusted.

The GLCM data points and the data points extracted using Efficient-Net are combined and fetched to optimization level.

C. Feature Optimization

In this step the most wanted and eligible data points are selected. The selection of optimized data points is performed using improved firefly algorithm. The concept of Firefly Algorithm (FA) is used to select the best data points for analysis of road surface condition.

The FA is inspired by the fireflies with flashing behaviour of light. The process of firefly is shown in Fig. 4. The extracted data points are set as feature vectors and fireflies are initialized for process of obtaining optimized feature set. Each firefly is said to be the potential feature subset. The brightness concepts of firefly are involved and is measures how well the classifications of roads condition is performed. The fitness function needs to evaluated and is given in Eq. (1).

$$Fitness = \alpha \times acc - \beta \times \frac{No\ of\ features}{Total\ features} \tag{1}$$

where: *acc* is the classification accuracy using selected data points. The number of data points is the data points selected by firefly. Total data points are the total number of data points extracted before selection. α and β are the weight parameters.

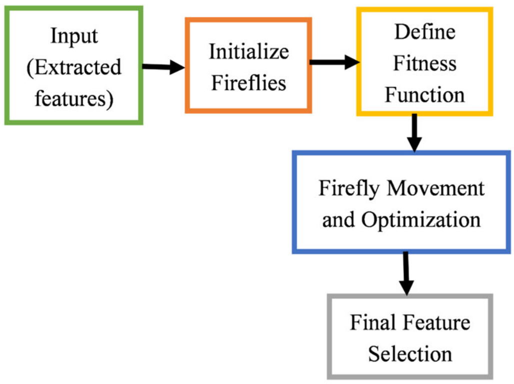

Fig. 4. Process of FA.

The brighter the fireflies (better solutions) attract others. The movement of fireflies adjusts the selected feature subset. The process repeats until an optimal subset is found. Select the best feature subset for classification. By this step it can be shown that the identification of RSC can be achieved utilized lower number of data points. These optimized are fetched to classifier.

D. Classification

The reduced data points are classified using SVM classifier. SVM is one of the most successful classifiers in many applications [34]. The data is split into training and testing with a ratio of 80:20. The data considered is linearly separable hence linear kernel function is utilized for distribution of data. A radial basis function kernel type is utilized. Finally, an optimal hyper plane is identified using the trained dataset and support vector across the hyperplane are identified. The model trained now predicts the labels for new data and shows the road surface output. The classification performance is evaluated by finding the parameters.

Pseudo code of proposed model is given below:

Pseudo code of proposed model
Input: Road surface image (I) **Output**: Predicted road surface class (Label) **Procedure**: 1. Extract W_feat using Wavelet Transform on I. 2. Extract G_feat using GLCM on I. 3. Extract E_feat using Efficient-Net on I. 4. Combine features: Combined_feat = W_feat + G_feat + E_feat. 5. Optimize features using Firefly Algorithm → F_feat. 6. Classify using SVM → Label. **Return Label**

IV. Experimental Findings

Zhao and Wei [32] discussed the experimental is conduction of road surface image dataset discussed. The dataset consists of different images with 27 sub categories. This data is evaluated using system which is discussed below.

A. System Environment

The model is designed using specific processors which is shown in Table II.

TABLE II. SYSTEM SPECS

Parameter	Config
OS	Windows11
Processor	Intel i10
Graphic Card	NVIDIA RTX 3080 GPU
RAM	64GB
Memory	1TB

The design utilizes the image processing tools, neural network tool box for training of designed model. The study considered some of the hyper parameters and learning rates for evaluating the proposed model. The parameters utilized is shown in Table III.

TABLE III. HYPERPARAMETERS UTILIZED

Parameter	Value
Learning rate	0.001
Batch size	32
Number of epochs	100
Dropout rate	0.3
Activation function	SiLU
Image size	224×224
Stride	2
Average Interference time	45 ms/image

B. Evaluation Metrics

The parameter needs to be evaluated as these parameters decides the effectiveness of the model designed. The metrics showcased are sensitivity, specificity, precision, accuracy and PBIAS. The values are achieved for the images that are processed using the model designed. All the parameter evaluated and its equations is shown in Table IV.

TABLE IV. METRICS EVALUATED

Parameter	Formula
Sensitivity	$Se = \frac{TP}{TP + FN}$
Specificity	$Sp = \frac{TN}{TN + FF}$
Precision	$Pe = \frac{TP}{TP + FP}$
Accuracy	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$
PBIAS	$PBIAS = 100 \times \frac{\sum (Y_{pre} - Y_{obs})}{\sum Y_{obs}}$

C. Results and Discussion

The input dataset is processed and trained using deep learning model, optimized using Firefly algorithm and finally classified using SVM learning model. The processing of input image and its results obtained is shown in Fig. 5.

Fig. 5 shows the identification of road condition depending on the input given for the system processing. Different road condition images are tested and trained using the machine learning model to achieve the accurate detection output. The proposed Wavelet, GLCM, Efficient-Net, Firefly optimized-Support Vector Machine (WGEF-SVM) model presents a novel and effective solution for RSC identification, particularly with its high accuracy and hybrid framework. For the given input image, the road condition output is identified by the proposed model. The classified image of the road surface condition is designed using Efficient-Net model in Matlab. The area needs to be identified based on various data points like colour, texture for the given input image with dry, wet, muddy, and snowy conditions. The results of classification performed is evaluated using the assessment of the metric. The assessed metrics values are shown in Table V.

TABLE V. RESULTS OF ASSESSED METRICS

Parameter/Model	CNN	GHR-50 [35]	Proposed WGEF
Accuracy	96.44	97.39	99.38
Specificity	96.13	97.16	99.32
Sensitivity	96.40	97.41	99.40
Precision	96.25	97.28	99.36
PBIAS error	0.255	0.134	0.0687
No of data points	1000	1349	675

In many applications, the accuracy and time for detection of classified image are considered. Using the proposed design the accuracy obtained is 99.38% as shown in Table V. From Table V it is shown that even in reduced number of data points the detection accuracy of designed work is good compared to Convolutional Neural Network (CNN) and other GLCM-Histogram-ResNet 50 (GHR-50) model [35]. The accuracy metric Confusion Matrix is shown in Fig. 6.

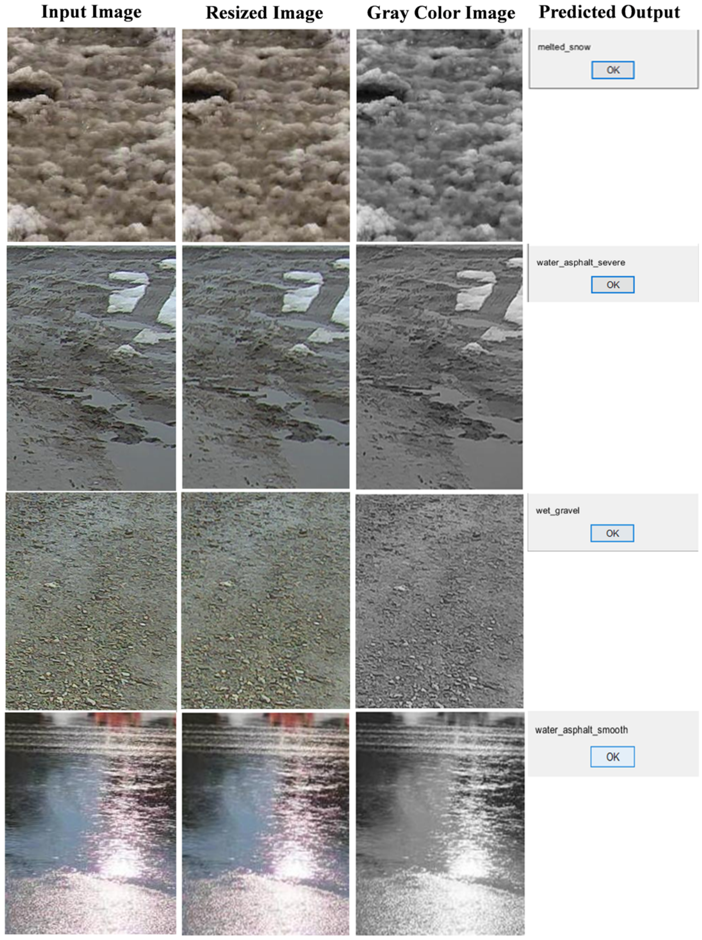

Fig. 5. Output prediction using proposed model.

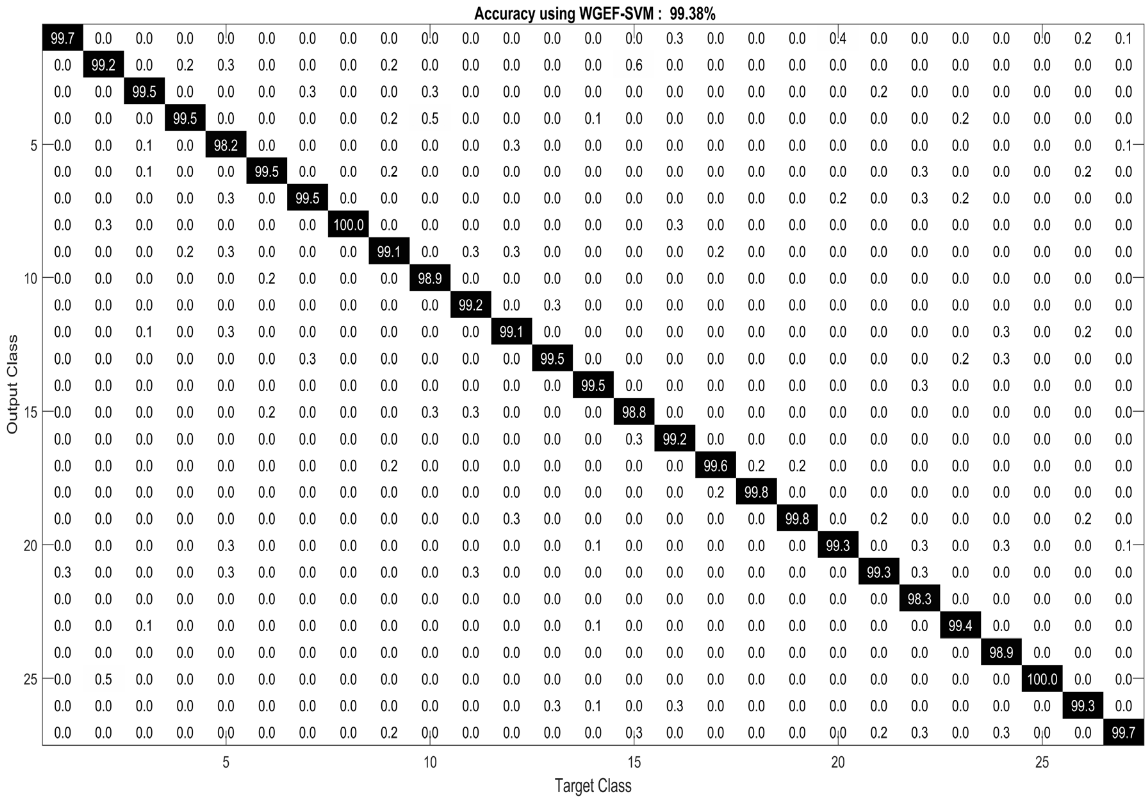

Fig. 6. Confusion Matrix using proposed WGEF model.

For the evaluated metrics obtained radar chart is shown in Fig. 7. The radar chat using Matlab is shown below. The value is plotted along each axis, and the points are connected to form a shape.

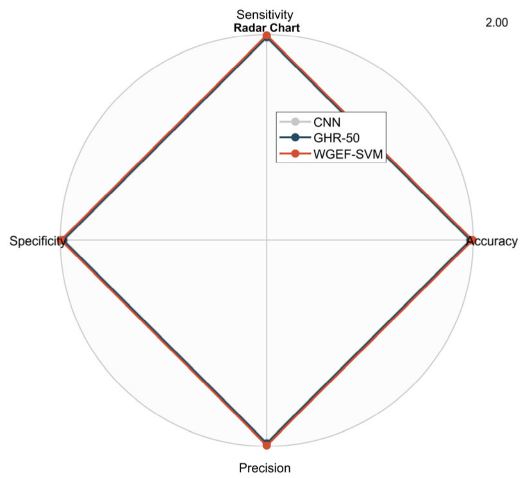

Fig. 7. Radar chart.

The Confusion Matrix achieved is used to validate the results and to show the efficacy of the designed model. A Confusion Matrix is produced to visually interpret the model's outputs to receive a summary of the outcomes on a classification issue. It summarizes the right and unsuccessful predictions according to class. After the showcase of confusion matrix, Receiver Operating Characteristic (ROC) curve under the area is evaluated on the test data and represented for different models as shown in Fig. 8. ROC curve achieved is with respect to false positive rate and true positive rate. The performance of the proposed WGEF-SVM model was further evaluated using the ROC curve, which provides a comprehensive view of the trade-off between sensitivity (True Positive Rate) and specificity (False Positive Rate) across various classification thresholds. High True Positive Rate (TPR) at low False Positive Rate (FPR) in the ROC curve demonstrates that the proposed model maintains high sensitivity without compromising specificity. The ROC curve analysis validates the efficiency of proposed model and is best compared to existing models.

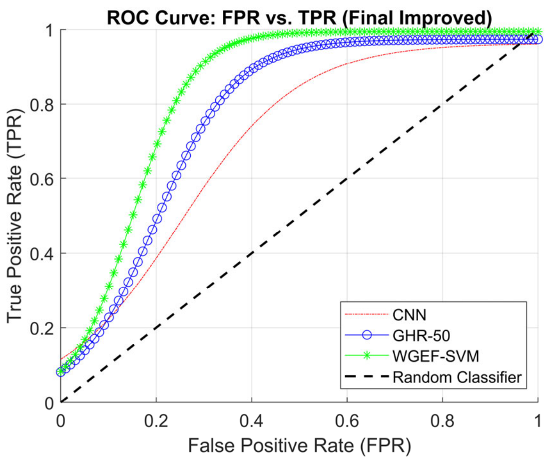

Fig. 8. ROC curve using different models.

The results of all models are judged with a random classifier. The model accuracy while performing training on the dataset is shown in Fig. 9.

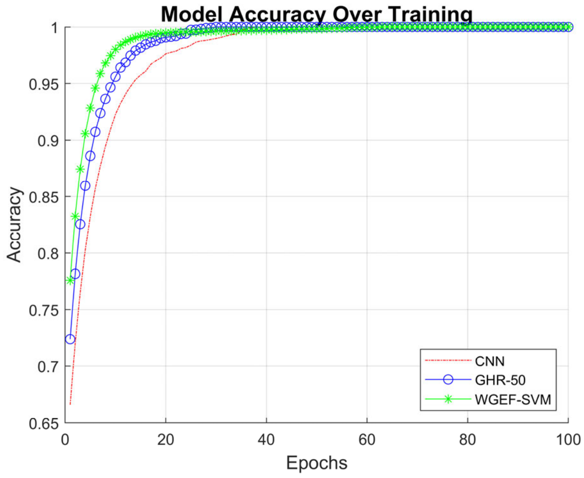

Fig. 9. Model accuracy over training.

The model accuracy is evaluated w.r.t to the epochs which refers to identify the performance of the classification model. After every epoch the model will update the parameters and verifies the accuracy. By epoch 5, the model crossed the 90% accuracy threshold, indicating that the combination of Wavelet, GLCM, and deep features began effectively capturing the road surface patterns. Between epochs 5–10, accuracy stabilized above 95%, showing that the model learned robust discriminative features. At around epoch 20, the model achieved a peak validation accuracy of 99.38%, suggesting near-perfect recognition of road surface conditions. Loss of information while performing the training of classifier w.r.t the epoch is shown in Fig. 10.

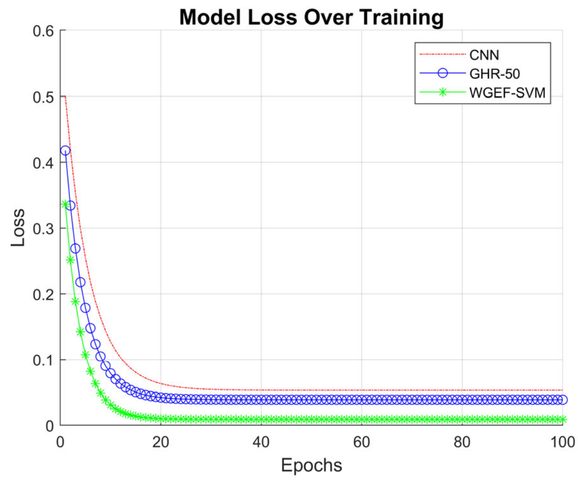

Fig. 10. Model accuracy over training.

The testing accuracy of the model is evaluated and is shown in Fig. 11.

Loss of information while performing the testing of classifier w.r.t the epoch is shown in Fig. 12.

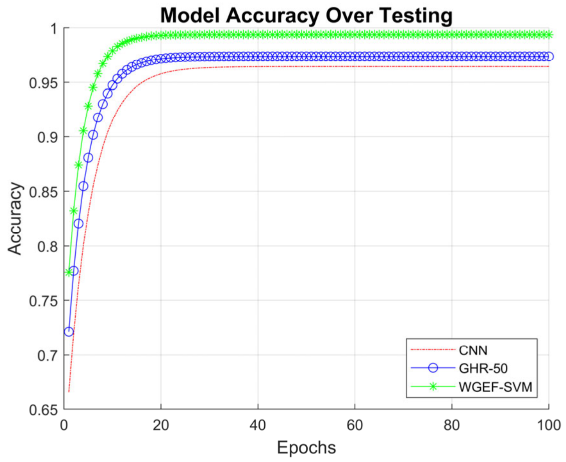

Fig. 11. Model accuracy over testing.

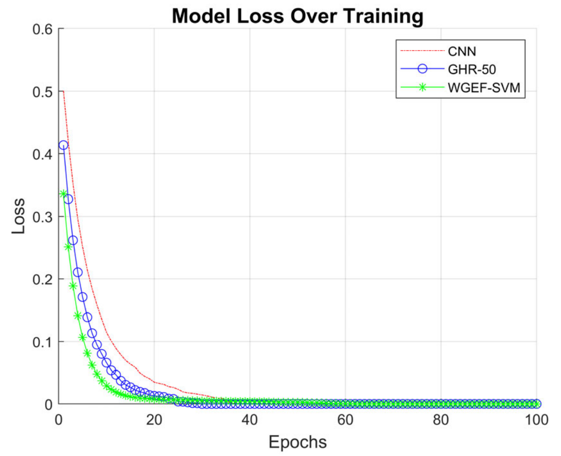

Fig.12. Model loss over testing.

The loss is low in the proposed WEGF-SVM model when compared to other techniques. The goal of the training model is to minimize the loss. Comparative analysis with state-of-art models is shown in Table VI.

TABLE VI. COMPARISON WITH EXISTING MODELS

Ref	Model utilized	Accuracy (%)
[36]	Canny Edge and Hough transform	90
[37]	SVM	88
[38]	PSO and SVM	90
[39]	NewReLU	94.9
[40]	VGG-SVM	91.8
[41]	R101- FPN	92.5
[42]	MLP-MMT	95.6
[35]	GHR50-SVM	97.39
Proposed	**WGEF**	**99.38**

The proposed model surpasses all the existing model in terms of identification of road surface condition more accurately as shown in Table VI and provide higher advantage for autonomous driving in different road conditions. Kim and Won [37] achieved an accuracy of 88% using SVM. PSO combined with SVM achieved an accuracy of 90% [38]. Implementing deep learning alone obtained accuracy of 94.9% [39]. The proposed model combined different models and achieved a higher accuracy of 99.38%. The comparative analysis is performed on the same dataset. The limitation of the work is in terms of detection time. Although detection time has not yet been fully optimized, future work will focus on making the model lightweight by incorporating pruning and quantization techniques. These optimizations are expected to significantly enhance inference speed and deploy ability on edge devices.

V. CONCLUSION

The overall study evaluates the accuracy of RSC identification using a hybrid approach that combines deep learning, optimization, and machine learning models. The deep learning component demonstrates strong recognition capabilities, and when integrated with machine learning techniques, it effectively addresses the challenges associated with RSC classification. The dataset proposed by T. Zhao is used to evaluate the performance of our designed model. Initially, the images in the dataset are pre-processed using Wavelet Transform, followed by the extraction of features using Gray Level Co-occurrence Matrix (GLCM) and Efficient-Net-based deep features. The extracted features are then optimized and reduced using the Firefly Algorithm, and final classification is performed using a Support Vector Machine (SVM) classifier. The effectiveness of the proposed model is validated through training analysis, loss evaluation, and generalization assessment using a confusion matrix. The proposed WGEF-SVM model achieves a high classification accuracy of 99.38%.

In future work, efforts can be directed towards optimizing the recognition time to enable real-time detection, which is essential for applications in autonomous vehicles and intelligent transportation systems. Additionally, expanding the dataset by incorporating road surface images from diverse geographic regions and varying environmental conditions will help improve the generalization ability of the model.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ramya K. Rajavolu conducted the research work, collected the data, and wrote the paper. Nutakki Jyothi supervised the work; all authors had approved the final version.

REFERENCES

[1] A. Bhatt, S. Bharadwaj, V. B. Sharma, R. Dubey, and S. Biswas, “An overview of road health monitoring system for rigid pavement by terrestrial laser scanner,” *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. 43, no. B1, pp. 173–180, 2022.

[2] S. Tilon, F. Nex, G. Vosselman, *et al*, “Towards improved unmanned aerial vehicle edge intelligence: A road infrastructure monitoring case study,” *Remote Sens.*, vol. 14, no. 16, 2022. doi: 10.3390/rs14164008

[3] E. A. Martinez-Ríos, M. R. Bustamante-Bello, and L. A. Arce-Sáenz, “A review of road surface anomaly detection and classification systems based on vibration-based techniques,” *Appl. Sci.*, vol. 12, no. 19, 2022. doi.org/10.3390/app12199413

[4] S. K. Sharma, H. Phan, and J. Lee, “An application study on road surface monitoring using DTW based image processing and

ultrasonic sensors," *Appl. Sci.*, vol. 10, no. 13, 2020. doi: 10.3390/app10134490

[5] A. Alrajhi, K. Roy, L. Qingge, and J. Kribs, "Detection of road condition defects using multiple sensors and IoT technology: A review," *IEEE Open J. Intell. Transp. Syst.*, vol. 4, pp. 372–392, 2023. doi: 10.1109/OJITS.2023.3237480

[6] A. Basavaraju, J. Du, F. Zhou, and J. Ji, "A machine learning approach to road surface anomaly assessment using smartphone sensors," *IEEE Sens. J.*, vol. 20, no. 5, pp. 2631–2638, 2020. doi: 10.1109/JSEN.2019.2952857

[7] M. S. Rao, C. Sekhar, and D. Bhattacharyya, "Comparative analysis of machine learning models on loan risk analysis," *Adv. Intell. Syst. Comput.*, vol. 1271, pp. 81–90, 2021. doi: 10.1007/978-981-15-9516-5_7

[8] T. S. Riyandi, A. Arif, and Widodo, "Classification of damaged road images using the convolutional neural network method," *Telemat. J. Inform. Dan Teknol. Inf.*, vol. 19, no. 2, pp. 147–158, 2022. doi: 10.31515/telematika.v19i2.6460

[9] S. A. Hassan, T. Rahim, and S. Y. Shin, "An improved deep convolutional neural network-based autonomous road inspection scheme using unmanned aerial vehicles," *Electronics*, vol. 10, no. 22, 2021. doi: 10.3390/electronics10222764

[10] D. Joshi, T. P. Singh, and G. Sharma, "Automatic surface crack detection using segmentation-based deep-learning approach," *Eng. Fract. Mech.*, vol. 268, 2022. doi: 10.1016/j.engfracmech.2022.108467

[11] I. Abdić, L. Fridman, D. E. Brown, *et al*., "Detecting Road surface wetness from audio: A deep learning approach," in *2016 23rd International Conference on Pattern Recognition (ICPR)*, 2016, pp. 3458–3463.

[12] M. Nolte, N. Kister, and M. Maurer, "Assessment of deep convolutional neural networks for road surface classification," arXiv preprint, arXiv:1804.08872v2, 2018.

[13] J. Carrillo and M. Crowley, "Integration of roadside camera images and weather data for monitoring winter road surface condition," in *Proc. 29th CARSP Conf.*, 2019, p. 12165.

[14] J. Carrillo, M. Crowley, and G. Pan, "Design of efficient deep learning models for determining road surface condition from roadside camera images and weather data," in *Proc. 2019 TAC-ITS Canada Joint Conf.*, 2020, p.10282.

[15] J. W. Seo, J. S. Kim, J. H. Yang, and C. C. Chung, "Classification method of road surface condition and type with LiDAR using spatiotemporal information," arXiv preprint, arXiv:2308.05965v1, 2023.

[16] H. Dong, K. Song, Y. He, *et al*., "PGA-Net: Pyramid feature fusion and global context attention network for automated surface defect detection," *IEEE Trans. Ind. Informat.*, vol. 16, no. 12, pp. 7448–7458, 2020. doi: 10.1109/TII.2019.2958826

[17] D. R. Sulistyaningrum, S. A. M. Putri, B. Setiyono, *et al*., "Classification of damaged road types using multiclass Support Vector Machine (SVM)," *J. Phys.: Conf. Ser.*, vol. 1821, 2021. doi: 10.1088/1742-6596/1821/1/012048

[18] Q. Wang, J. Mao, X. Zhai, *et al*., "Improvements of YOLOv3 for road damage detection," *J. Phys.: Conf. Ser.*, vol. 1903, No. 1, p. 012008, 2021.

[19] L. Guo, R. Li, and B. Jiang, "A road surface damage detection method using yolov4 with PID optimizer," *Int. J. Innov. Comput. Inf. Control*, vol. 17, no. 5, pp. 1763–1774, 2021.

[20] M. Li, H. Wang, Y. Peng, *et al*., "Edge-to-client real-time road damage detection system based on Yolov5," in *Proc. 2021 China Autom. Congr. (CAC)*, 2021, pp. 1221–1226.

[21] D. Jeong and J. Kim, "Road damage detection using YOLO with image tiling about multi-source images," in *Proc. 2022 IEEE Int. Conf. Big Data (Big Data)*, 2022, pp. 6401–6406.

[22] P. N. Srinivasu, G. L. A. Kumari, S. C. Narahari, *et al*., "Exploring the impact of hyperparameter and data augmentation in YOLOv10 for accurate bone fracture detection from X-ray images," *Sci. Rep.*, vol. 15, no. 1, p. 9828, 2025. doi: 10.1038/s41598-025-93505-4

[23] S. Naddaf-Sh, M. M. Naddaf-Sh, A. R.Kashani, *et al*., "An efficient and scalable deep learning approach for road damage detection," in *Proc. 2020 IEEE Int. Conf. Big Data (Big Data)*, 2020, pp. 5602–5608.

[24] D. Arya, *et al*., "Deep learning-based road damage detection and classification for multiple countries," *Autom. Constr.*, vol. 132, p. 103935, 2021.

[25] V. Hegde, H. Maeda, S. K. Ghosh, *et al*., "Yet another deep learning approach for road damage detection using ensemble learning," in *Proc. 2020 IEEE Int. Conf. Big Data (Big Data)*, 2020, pp. 5553–5558.

[26] D. Arya, H. Maeda, S. K. Ghosh, *et al*., "RDD2022: A multi-national image dataset for automatic road damage detection," *Geoscience Data Journal*, vol. 11, no. 4, pp. 846–862, 2024.

[27] V. Pham, N. Nguyen, and C. Donan, "Road damage detection and classification with YOLOv7," in *Proc. 2022 IEEE Int. Conf. Big Data (Big Data)*, 2022, pp. 6416–6423.

[28] X. Wang, H. Gao, Z. Jia, and Z. Li, "BL-YOLOv8: An improved road defect detection model based on YOLOv8," *Sensors*, vol. 23, no. 20, p. 8361, 2023.

[29] M. A. Benallal and M. S. Tayeb, "An image-based convolutional neural network system for road defects detection," *IAES Int. J. Artif. Intell.*, vol. 12, no. 2, pp. 577–586, 2023.

[30] A. Hadj-Attou, Y. Kabir, and F. Ykhlef, "Hybrid deep learning models for road surface condition monitoring," *Measurement*, vol. 220, p. 113267, 2023. doi: 10.1016/j.measurement.2023.113267

[31] K. H. Almotairi, "Hybrid adaptive method for lane detection of degraded road surface condition," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 34, no. 8, pp. 5261–5272, 2022. doi: 10.1016/j.jksuci.2022.06.008

[32] T. Zhao and Y. Wei, "A road surface image dataset with detailed annotations for driving assistance applications," *Data Brief*, vol. 43, p. 108483, 2022. doi: 10.1016/j.dib.2022.108483

[33] A. Aziz and F. Putra, "Effect of features and angle on GLCM feature extraction on accuracy for object classification," *SMARTICS J.*, vol. 8, no. 2, pp. 24–30, 2022. doi: 10.21067/smartics.v8i2.7627

[34] P. K. Sekharamantry, M. S. Rao, Y. Srinivas, and A. Uriti, "PSR-LeafNet: A deep learning framework for identifying medicinal plant leaves using support vector machines," *Big Data Cogn. Comput.*, vol. 8, no. 12, p. 176, 2024. doi: 10.3390/bdcc8120176

[35] R. R. Krishna and N. Jyothi, "Road surface condition identification with deep neural networks and SVM classifier," *Eng., Technol. Appl. Sci. Res.*, vol. 15, no. 2, pp. 21998–22003, 2025. doi: 10.48084/etasr.10166

[36] A. Raj, D. Krishna, K. Shantanu, *et al*., "Vision based road surface detection for automotive systems," in *Proc. 2012 Int. Conf. Appl. Electron.*, 2012, pp. 223–228.

[37] J. H. Kim and J. M. Won, "A development of the road surface decision algorithm using SVM (Support Vector Machine) clustering methods," *J. Korea Inst. Intell. Transp. Syst.*, vol. 12, no. 5, pp. 1–12, 2013.

[38] J. Zhao, H. Wu, and L. Chen, "Road surface state recognition based on SVM optimization and image segmentation processing," *J. Adv. Transp.*, vol. 2017, p. 6458495, 2017. doi: 10.1155/2017/6458495

[39] L. Cheng, X. Zhang, and J. Shen, "Road surface condition classification using deep learning," *J. Vis. Commun. Image Represent.*, vol. 64, p. 102638, 2019. doi: 10.1016/j.jvcir.2019.102638

[40] J. Carrillo, M. Crowley, G. Pan, and L. Fu, "Design of efficient deep learning models for determining road surface condition from roadside camera images and weather data," arXiv preprint, arXiv:2009.10282, 2020.

[41] S. Lee, J. Jeon, and T. H. M. Le, "Feasibility of automated black ice segmentation in various climate conditions using deep learning," *Buildings*, vol. 13, no. 3, p. 767, 2023. doi: 10.3390/buildings13030767

[42] Y. Moroto, K. Maeda, R. Togo, *et al*., "Multimodal transformer model using time-series data to classify winter road surface conditions," *Sensors*, vol. 24, no. 11, p. 3440, 2024. doi: 10.3390/s24113440