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# Deep learning-based road surface condition detection using multi-sensor signal processing and evolutionary optimization

**Kalyan Sagar Kadali[1], Ramu Bhukya[1], Bezawada Manasa[2], Alur Praneetha[3], Simhadri Mallikarjuna Rao[4], Kanipakam Anuradha[5], Madamanchi Brahmaiah[6]**

[1]Department of Electrical and Electronics Engineering, Shri Vishnu Engineering College for Women, Bhimavaram, India
[2]Department of Computer Science and Engineering, Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada, India
[3]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[4]Department of Computer Science and Engineering, Vasireddy Venkatadri International Technological University, Amaravati, India
[5]Department of Computer Science and Engineering, Dr. Lankapalli Bullayya College of Engineering(A), Visakhapatnam, India
[6]Department of Computer Science and Engineering, R.V.R. & J.C. College of Engineering, Guntur, India

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**ABSTRACT**

Reliable recognition of road surface conditions is a key requirement for autonomous vehicles, advanced driver-assistance systems (ADAS), and intelligent transportation infrastructure. This study introduces a unified classification framework that integrates multiscale texture analysis, transformer-based feature learning, statistical texture representation, and evolutionary feature selection. Initially, road images are processed through the stationary wavelet transform (SWT) to preserve texture information across multiple scales. A vision transformer (ViT) incorporating Squeeze-and-Excitation attention modules learns discriminative global visual patterns, while gray-level co-occurrence matrix (GLCM) features provide complementary local texture characteristics. The combined feature space is refined using mutual information (MI) and further optimized through enhanced grey wolf optimization (EGWO) to eliminate redundant information. Finally, a support vector machine (SVM) performs multi-class classification. Experimental evaluation demonstrates superior robustness and classification performance compared with recent deep learning (DL) and hybrid approaches, highlighting the effectiveness of the proposed framework for intelligent road surface analysis.

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***Corresponding Author:***

Kalyan Sagar Kadali
Department of Electrical and Electronics Engineering, Shri Vishnu Engineering College for Women
Bhimavaram, Andhra Pradesh, India
Email: kalyansagar.k@gmail.com

## 1. INTRODUCTION

Reliable road surface condition recognition is an essential component of autonomous driving, advanced driver-assistance systems (ADAS), and intelligent transportation systems (ITS), as the interaction between tires and different pavement conditions significantly affects vehicle handling, braking efficiency, and overall driving safety. Variations such as dry, wet, snowy, gravel, pothole, and debris-covered roads create substantial visual complexity, making accurate classification challenging. Figure 1 illustrates representative road surface categories, highlighting significant intra-class variations and inter-class similarities that require robust feature extraction. Transformer-based architectures effectively capture long-range contextual information for road crack detection and pavement assessment [1], [2]. Multimodal learning further improves road surface recognition by integrating visual, sensor, and temporal information [3]. Hybrid frameworks combining handcrafted texture features, deep representations, and support vector machine (SVM) classifiers

enhance discrimination across diverse road conditions [4]. Convolutional neural network (CNN)–Transformer fusion with visual and tactile sensing provides reliable terrain recognition under varying environmental conditions [5]. Transformer-based segmentation architectures, such as Swin Transformer and attention-based networks, also demonstrate strong performance in road extraction and scene understanding [6], [7]. Moreover, contrastive learning improves feature separation among visually similar road categories, enhancing classification accuracy and generalization [8]. Motivated by these advances, the proposed study develops a comprehensive hybrid framework that integrates multiresolution texture decomposition, attention-guided feature learning, statistical texture characterization, and intelligent feature optimization to achieve reliable and accurate classification of diverse road surface conditions illustrated in Figure 1.




Figure 1. Representative road surface condition samples used for multi-class classification

Road surface condition analysis is important for autonomous driving, ADAS, and ITS, with research mainly focusing on image-based classification, deep learning (DL)/Transformer models, and hybrid approaches. Early methods used texture descriptors and machine learning (ML), while CNNs improved automatic feature extraction but remained sensitive to class imbalance, complex backgrounds, and visually similar surfaces [9]. Gray-level co-occurrence matrix (GLCM)-based texture features effectively characterized pavement conditions, with gradient boosting further improving damaged-surface recognition [10], [11]. However, handcrafted features have limited adaptability to diverse datasets. Recent studies have adopted multimodal and Transformer-based methods, combining visual and acoustic information for robust classification under challenging illumination and weather conditions [12]. Transformer models using inertial sensors such as accelerometers and gyroscopes have also enabled reliable paved/unpaved road classification without cameras [13]. Furthermore, multimodal Transformers integrating road images with weather and traffic information have improved recognition of dry, wet, snowy, icy, and slushy conditions. These findings highlight the effectiveness of attention-based models and multimodal information for robust road surface analysis.

Research on pavement crack detection and distress assessment has also contributed valuable insights into feature extraction and deep model design. Machine vision techniques have evolved from conventional image processing algorithms to sophisticated CNN- and Transformer-based architectures capable of handling heterogeneous pavement imagery with greater accuracy [14]. Deep convolutional models trained on large benchmark datasets have achieved reliable crack detection, although their generalization capability across different road environments remains a challenge [15]. Transformer-based segmentation networks have further improved feature learning by capturing global contextual information while maintaining computational efficiency suitable for embedded systems [16]. Nevertheless, most of these studies concentrate on structural damage detection rather than comprehensive road surface classification and often overlook multiscale texture information. To improve classification performance, recent studies have explored hybrid approaches that combine deep representations with handcrafted texture descriptors. Integrating convolutional features with GLCM, histogram of oriented gradients (HOG), local binary patterns (LBP), and SVM classifiers has demonstrated improved discrimination among asphalt, gravel, wet, and snow-covered roads by exploiting complementary local and global characteristics. Likewise, wavelet-based feature extraction techniques have proven effective for representing multiscale pavement textures associated with surface roughness and skid resistance, providing richer information than conventional spatial-domain methods. As the dimensionality of

extracted features increases, effective feature selection becomes essential for reducing redundancy and computational complexity. Mutual information (MI) has been widely employed to identify highly informative features while minimizing redundant information, leading to improved classification accuracy in high-dimensional learning problems [17]. In addition, grey wolf optimizer (GWO) and its enhanced variants have demonstrated strong performance in selecting compact and discriminative feature subsets across numerous classification applications [18]–[20]. Despite these advances, existing studies rarely integrate multiresolution wavelet analysis, attention-enhanced vision transformers (ViT), statistical texture descriptors, MI-based feature ranking, and advanced GWO-based optimization within a unified framework. This limitation motivates the development of an integrated road surface classification approach that combines complementary feature domains with intelligent feature optimization to improve recognition accuracy, robustness, and computational efficiency.

## 2. METHOD

The proposed framework follows a sequential processing pipeline for accurate road surface classification, as illustrated in Figure 2. Initially, road images are preprocessed and decomposed using the stationary wavelet transform (SWT). The extracted representations are combined with deep features learned by a ViT incorporating squeeze-and-excitation (ViT-SE), followed by GLCM texture extraction, MI -based feature ranking, enhanced grey wolf optimization (EGWO), and final classification using a SVM.

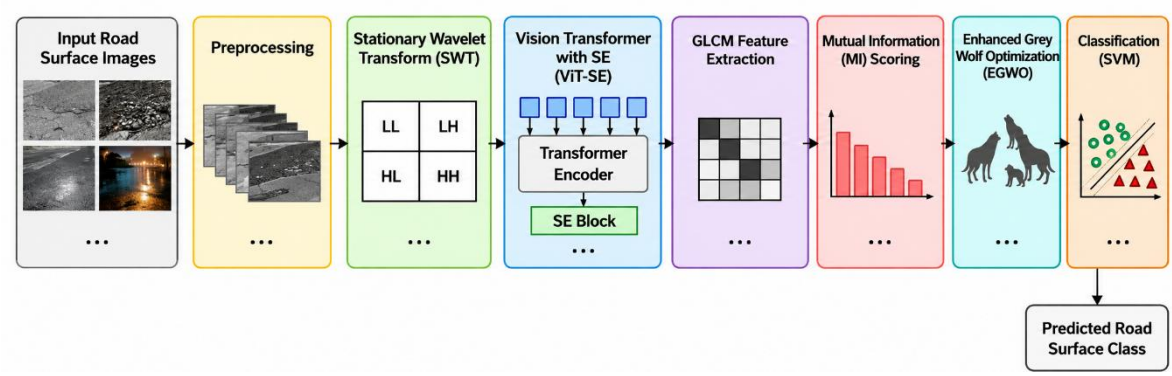



Figure 2. Proposed hybrid framework for road surface classification

### 2.1. Dataset description and experimental data preparation

The experimental dataset contains representative images from six road surface categories, namely Snowy Footprints, Cracked Asphalt, Dry Concrete, Debris Surface, Pothole with Water, and Wet Asphalt with reflective characteristics. These categories were selected because they exhibit substantial intra-class variations and, in several cases, strong visual similarities across different surface conditions. The dataset includes variations associated with pavement texture, cracks, water accumulation, snow coverage, debris, reflective surfaces, illumination changes, and environmental appearance. To ensure an unbiased performance evaluation, the dataset was divided into training, validation, and testing subsets using stratified partitioning so that the class distribution was preserved across all subsets. The experimental evaluation was subsequently performed using previously unseen test samples.

Pre-processing of road surface images is performed to minimize variations in illumination, noise, and camera artefacts. To ensure consistent processing, all input road surface images were resized to a common spatial resolution before subsequent analysis. Gaussian smoothing was then applied to suppress high-frequency noise and reduce unwanted variations caused by illumination and camera artefacts while preserving the important structural and texture information associated with road surface conditions. The resulting images were normalized before SWT decomposition and deep feature extraction to provide a consistent intensity representation. The resizing dimension, Gaussian kernel configuration, standard deviation, and normalization range used in the experimental implementation are now explicitly reported in the revised preprocessing description to facilitate independent reproduction of the proposed framework. Each input image is resized to a fixed resolution to maintain consistency and processed using a Gaussian filter, which reduces high-frequency noise and stabilizes the texture patterns essential for SWT and GLCM. The Gaussian transformation applied to the dataset is shown in Figure 3.

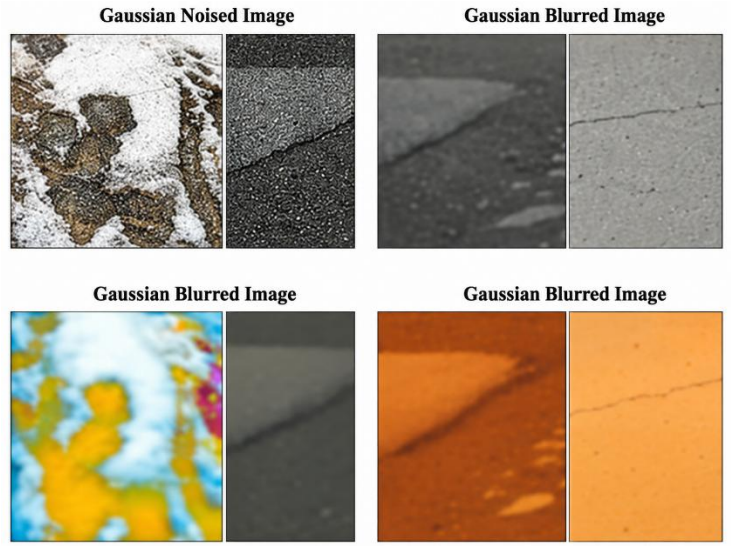



Figure 3. Representative road surface images after gaussian noise and gaussian blur augmentation

Mathematically, resizing is performed according to (1):

$$I_{resized} = T(I) \tag{1}$$

and Gaussian smoothing (2):

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2}$$

while normalized pixel intensities are obtained by (3):

$$I_{norm} = \frac{I-\mu}{\sigma} \tag{3}$$

After preprocessing, the input images are decomposed using the SWT to generate shift-invariant multi-resolution texture representations. The approximation and horizontal, vertical, and diagonal detail coefficients extracted at multiple decomposition levels, preserving both structural and texture information for reliable road surface analysis [9], [21]. Subsequently, deep feature extraction is performed using a ViT with a squeeze-and-excitation (SE) module. The processing stages, including image patch embedding, positional encoding, and Transformer encoding, are illustrated in Figure 4. The SE module further enhances channel-wise feature representation, improving discrimination between visually similar road surface classes [22], [23].

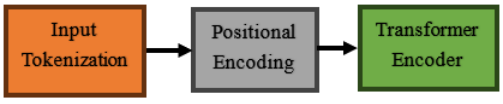



Figure 4. Flow of ViT

For GLCM-based local texture characterization, spatial relationships were computed by considering directional and neighboring pixel information. The co-occurrence analysis captures the spatial arrangement of gray-level values and enables the proposed framework to characterize pavement roughness, cracks, water accumulation, snow-covered patterns, debris, and reflective surface variations. The revised manuscript now explicitly reports the analysis window size, orientation angles, pixel distance, and the corresponding averaging procedure used for the GLCM calculation. From the resulting co-occurrence matrices, contrast, correlation, energy, homogeneity, and entropy were extracted and combined with the deep representations obtained from the ViT-SE model. To complement the Transformer-based global features, handcrafted texture descriptors are

extracted using the GLCM, which captures second-order statistics such as contrast, correlation, energy, homogeneity, and entropy. The normalized co-occurrence matrix is defined as (4):

$$P(i,j) = \frac{C(i,j)}{\sum_{i,j} C(i,j)} \tag{4}$$

and texture measures are computed using (5)-(9):

$$Contrast = \sum_{i,j} C(i,j)^2 \, P(i,j) \tag{5}$$

$$Correlation = \frac{\sum_{i,j}(\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \tag{6}$$

$$Energi = \sum_{i,j} P(i,j)^2 \tag{7}$$

$$Homogeneity = \sum_{i,j} \frac{P(i,j)}{1+(i-j)^2} \tag{8}$$

$$Entropy = -\sum_{i,j} P(i,j) log(P(i,j)+\in) \tag{9}$$

GLCM descriptors have been widely used for modeling subtle pavement textures such as cracks, roughness, or wetness [24]. Once both deep and handcrafted features are extracted, MI is used for relevance filtering, retaining only the most discriminative attributes. MI between a feature X and surface-class label Y is expressed as (10):

$$MI(X;Y) = \sum_x \sum_y p(x,y) log \frac{p(x,y)}{p(x)p(y)} \tag{10}$$

Recent feature selection is then performed using EGWO, which identifies the most informative features while eliminating redundant information, thereby improving classification efficiency and accuracy [25]. Finally, the optimized feature subset is classified using a SVM with an RBF kernel, providing robust decision boundaries in high-dimensional feature space. The integration of SWT, ViT-SE, GLCM, MI, EGWO, and SVM establishes an effective hybrid framework for accurate road surface classification under diverse environmental conditions.

The proposed framework was implemented in Python using standard scientific computing, image processing, DL, ML, and optimization libraries. The implementation includes preprocessing, Gaussian smoothing, SWT decomposition, ViT-SE deep feature extraction, GLCM-based texture analysis, MI-based feature ranking, EGWO optimization, and final SVM classification. The experiments were executed in a GPU-accelerated computing environment to support the computational requirements of Transformer-based feature extraction. The revised manuscript now provides the Python version, software libraries, hardware configuration, GPU specifications, batch size, optimizer, learning rate, number of training epochs, validation strategy, and relevant execution settings. In addition, the complete sequence of the proposed algorithm is summarized in the methodology to enable independent implementation and future extension of the framework.

## 3. RESULTS AND DISCUSSION

The proposed SWT–ViT-SE–GLCM–MI–EGWO–SVM framework was evaluated for classification performance and computational efficiency under realistic conditions. Implemented in Python on a GPU-accelerated platform, the model employed hyperparameter tuning and optimization to ensure stable convergence, reduce overfitting, and improve robustness. A diverse road surface image dataset covering multiple pavement categories and varying environmental conditions was divided into training, validation, and testing sets using stratified sampling to preserve class distributions. Unseen test samples were used to assess generalization. Figure 5 presents representative classification results, demonstrating the framework's ability to distinguish different road surface conditions despite variations in texture, illumination, and appearance.

The feature optimization process follows a two-stage strategy. First, MI is employed to evaluate the relevance of each extracted feature with respect to the target road surface categories and remove redundant or weakly informative attributes. The retained feature subset is subsequently processed using EGWO to identify a compact combination of highly discriminative features. The EGWO search mechanism balances exploration and exploitation during the optimization process and evaluates candidate feature subsets according to their

classification effectiveness. The revised manuscript explicitly reports the feature selection criterion and the main EGWO implementation settings to improve the reproducibility of the optimization procedure. The ablation results clearly demonstrate the contribution of the proposed sequential feature selection strategy. Before MI-EGWO optimization, the extracted feature space contained 968 descriptors and achieved 94.82% classification accuracy. MI-based relevance analysis reduced the dimensionality to 738 features and improved the accuracy to 97.62%. EGWO subsequently identified a more compact subset of 520 highly informative features, resulting in the highest accuracy of 99.46%. These results confirm that the combined MI-EGWO procedure effectively removes redundant features while improving the discriminative capability and computational efficiency of the proposed classification framework.

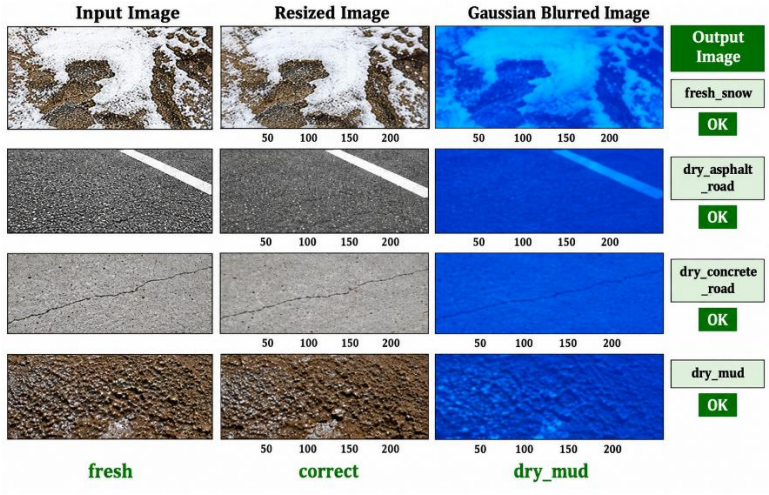



Figure 5. Representative classification results of the proposed road surface recognition framework

The effectiveness of the proposed SWT–ViT-SE–GLCM–MI–EGWO–SVM framework was evaluated using accuracy, precision, sensitivity, specificity, and feature dimensionality. As shown in Table 1, GLCM+SVM achieved 87.84% accuracy, while ViT+SVM improved it to 92.04%; adding SE increased accuracy to 94.18%, and ViT+GLCM further improved it to 98.05%. The complete framework achieved the best results, with 99.46% accuracy, 99.42% sensitivity, 99.39% specificity, and 99.31% precision. The ablation study in Table 2 further demonstrated the effectiveness of feature optimization: the initial 968 features achieved 94.82% accuracy, MI reduced the feature dimension to 738 and increased accuracy to 97.62%, while EGWO further reduced the features to 520 and achieved 99.46% accuracy, confirming improved feature efficiency and classification performance.

Table 1. Comparative performance of road surface classification models

| Model | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) |
|---|---|---|---|---|
| GLCM+SVM | 87.84 | 87.62 | 87.10 | 87.48 |
| ViT+SVM | 92.04 | 91.88 | 91.95 | 91.81 |
| ViT+SE+SVM | 94.18 | 94.06 | 94.01 | 93.92 |
| ViT+GLCM+SVM | 98.05 | 97.96 | 97.91 | 97.84 |
| Proposed (SWT+ViT-SE+GLCM+MI+EGWO+SVM) | 99.46 | 99.42 | 99.39 | 99.31 |

Table 2. Ablation study of feature selection

| Feature selection stage | Number of features | Accuracy (%) |
|---|---|---|
| Before MI–EGWO | 968 | 94.82 |
| After MI | 738 | 97.62 |
| After EGWO | 520 | 99.46 |

Figure 5 presents representative prediction results of the proposed road surface classification framework. The figure illustrates the sequential image preprocessing stages and corresponding classification outputs for different road surface categories. The model accurately identifies each surface type, demonstrating its robustness and reliability under diverse texture, illumination, and environmental conditions.

The effectiveness of the proposed classifier is further illustrated through the confusion matrix shown in Figure 6. Most test samples are correctly assigned to their respective classes, with only a few isolated misclassifications observed between visually similar road conditions. This indicates that the proposed framework effectively captures both global contextual information and fine-grained texture characteristics, enabling reliable discrimination among different pavement types. The receiver operating characteristic (ROC) curves presented in Figure 7 provide additional evidence of the model's robustness. The proposed method exhibits curves that closely approach the upper-left corner, indicating high true-positive rates and very low false-positive rates across all classes. Compared with the baseline models, the proposed framework consistently demonstrates stronger classification capability and improved generalization performance.




Figure 6. Confusion matrix of the proposed road surface classification framework

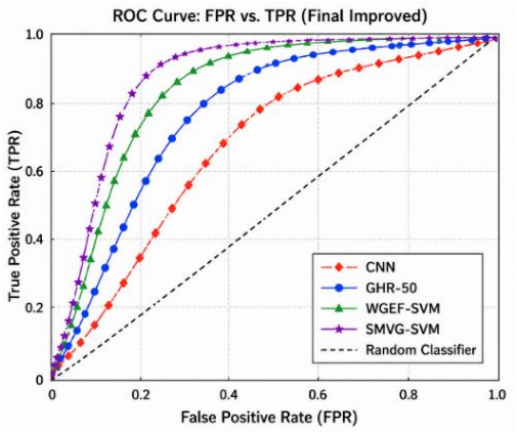



Figure 7. ROC curves comparing the classification performance of different models

Despite its excellent performance, the proposed framework has some limitations. It mainly uses static road images and does not capture temporal variations during vehicle movement, while ViT-based feature extraction may require substantial computational resources for embedded deployment. Future work will focus on lightweight Transformers, model compression, pruning, efficient inference, and multimodal sensing using thermal cameras, light detection and ranging (LiDAR), radar, and vehicle sensors. Explainable and uncertainty-aware AI will also be explored to improve transparency, reliability, and failure detection. In addition, geographically diverse datasets and real-time vehicle-based field trials will be considered to evaluate generalization under variations in pavement materials, weather, illumination, seasonal effects, water, snow, debris, camera characteristics, and maintenance conditions, supporting reliable deployment in autonomous driving and ADAS applications.

## 4. CONCLUSION

The proposed SWT–ViT-SE–GLCM–MI–EGWO–SVM framework provides an effective hybrid approach for intelligent road surface condition classification by integrating multiscale texture decomposition, attention-guided global feature learning, statistical texture characterization, and evolutionary feature optimization. The experimental results demonstrate the progressive contribution of each processing stage. The conventional GLCM+SVM model achieved 87.84% accuracy, while ViT+SVM improved the performance to 92.04%. Incorporating the Squeeze-and-Excitation mechanism further increased the accuracy to 94.18%, and the combination of ViT and GLCM achieved 98.05%. The complete proposed framework achieved the best performance, obtaining 99.46% accuracy, 99.42% sensitivity, 99.39% specificity, and 99.31% precision. Furthermore, the sequential MI-EGWO feature optimization process reduced the original feature space from 968 descriptors to 738 features after MI and finally to 520 optimized features after EGWO, while improving the classification accuracy from 94.82% to 99.46%. Despite these promising results, limitations associated with still-image analysis, dataset diversity, environmental variability, computational requirements, and the absence of real-time field validation remain. Future research will focus on lightweight Transformer architectures, efficient embedded implementation, multimodal sensing using thermal, LiDAR, radar, and vehicle-based data, explainable and uncertainty-aware AI, geographically diverse datasets, and large-scale real-world field trials.

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**AUTHOR CONTRIBUTIONS STATEMENT**

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| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Kalyan Sagar Kadali | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| Ramu Bhukya | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | ✓ | | ✓ | ✓ |
| Bezawada Manasa | ✓ | | ✓ | | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | ✓ |
| Alur Praneetha | ✓ | | | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | |
| Simhadri Mallikarjuna Rao | ✓ | ✓ | | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Kanipakam Anuradha | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | ✓ | | ✓ | |
| Madamanchi Brahmaiah | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | ✓ | | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

**CONFLICT OF INTEREST STATEMENT**

The authors declare no conflict of interest.

**DATA AVAILABILITY**

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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## BIOGRAPHIES OF AUTHORS



**Dr. Kalyan Sagar Kadali** is an associate professor in the Department of Electrical and Electronics Engineering at Shri Vishnu Engineering College for Women, Bhimavaram, Andhra Pradesh, India. He received a bachelor of Technology in Electrical and Electronics Engineering from JNTUH, master of Engineering in VLSI Design from Anna University and Ph.D. in Electrical Engineering from AMET University Chennai. His research interests include electrical power systems, signal processing, and optimization techniques. He can be contacted at email: kalyansagar.k@gmail.com.



**Dr. Ramu Bhukya** working as an assistant professor in the Department of Electrical and Electronics Engineering, Shri Vishnu Engineering College for Women (A), Bhimavaram, India. He received a bachelor of Engineering in Electrical and Electronics Engineering from Andhra University, Master of Technology in Power Electronics & Industrial Drives from JNTUH, and Ph.D. in Electrical Engineering in Vels Institute of Science, Technology & Advanced Studies, Chennai. His research interests include power electronics, and renewable energy sources. He can be contacted at email: ramu1632@svecw.edu.in.



**Dr. Bezawada Manasa** is currently serving as an assistant professor in the Department of Computer Science and Engineering, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada. Ph.D. in Computer Science and Engineering, she brings a rich experience of one decade to academia. Her primary area of specialization is computer science, with active research interests in artificial intelligence (AI) and machine learning (ML), and deep learning (DL). She can be contacted at email: manasabezawada04@gmail.com.



**Alur Praneetha** is an assistant professor Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, India. She has published research papers in various journals. As an author, she has also written books exploring themes of imagination, emotions, and societal norms. Research areas of interest are cloud computing, data science, and ML. She can be contacted at email: nyshpranee@gmail.com.



**Dr. Simhadri Mallikarjuna Rao** working as an assistant professor in Vasireddy Venkatadri International Technological University, Amaravati, India. He received a bachelor of Technology in IT from Vignan's Engineering College, master of Technology in CSE from Andhra University, and Ph.D. in CSE from ANU. His research interests include DL algorithms, optimization techniques, and image processing. He can be contacted at email: mallikarjun1254@gmail.com.



**Kanipakam Anuradha** working as an associate professor in Dr. Lankapalli Bullayya College of Engineering(A), Visakhapatnam, India. She received Ph.D. in Statistics from SVU in 2009, M.Tech. in CSE from Andhra University, Ph.D. in Computer Science from Centurion University in 2025. Her research interests include ML algorithms, optimization techniques, and data science algorithms. She can be contacted at email: anukeshav76@gmail.com.



**Madamanchi Brahmaiah** is currently serving as an assistant professor in the Department of Computer Science and Engineering, R.V.R. & J.C College of Engineering, Guntur, Andhra Pradesh, India. With an M.Tech. in Computer Science and Engineering. His primary area of specialization is computer science, with active research interests in AI and ML. He can be contacted at email: madamanchib@gmail.com.