Supervised Anomaly Detection for Features Extraction from Normal Semantics

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Abstract—In the realm of anomaly detection, identifying deviations from normal behavior in data is critical across various applications, including cybersecurity, manufacturing, and healthcare. Traditional supervised methods rely on labeled datasets, which are often scarce or expensive to obtain. To address this challenge, we propose supervised anomaly detection framework that leverages deep learning techniques to extract features from normal semantic patterns. Our approach integrates Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and ResNet-18 architectures to enhance the detection accuracy and efficiency. Initially, CNNs are employed to capture spatial hierarchies in the data, learning robust feature representations from normal samples. The extracted features are then fine-tuned using the ResNet-18 model, known for its depth and skip connections, to ensure comprehensive feature extraction and minimize information loss. Finally, these deep features are fed into an SVM to differentiate between normal and anomalous instances based on the learned semantics. Experimental results on benchmark datasets demonstrate the superiority of our method in detecting anomalies with high precision and recall, outperforming traditional anomaly detection techniques. Our framework's ability to operate without labeled anomalies and adapt to various domains underscores its potential for broad applicability in real-world scenarios.

Keywords— Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and ResNet-18 architectures, deep Learning.

I. INTRODUCTION

Concrete roads are integral to modern infrastructure, providing durable and reliable surfaces for vehicular traffic. However, over time, these surfaces are susceptible to various forms of degradation such as cracks, spalling, and potholes, which can compromise safety and efficiency. Finding visual data that dramatically deviates from usual cases is known as anomaly detection [1]. Anomaly detection is being used in many different applications, such as network security [8], defect detection [2], medical diagnostics [3], [4], video surveillance [5], [6], financial transaction monitoring [7], and video surveillance [8]. In the industrial domain, anomaly detection is especially useful for tasks like identifying conductive particles in glass chips [9] and examining steel surfaces [10].

Detecting these anomalies early is crucial for timely maintenance and prevention of more severe damage. supervised anomaly detection offers a promising alternative, as it does require labeled data for training. This approach can significantly enhance the efficiency and accuracy of road condition monitoring systems. The primary motivation behind this research is the need for a more efficient and effective method to monitor the health of concrete roads. Traditional inspection methods are not only resource-intensive but also prone to human error. Moreover, the use of supervised learning techniques for anomaly identification is constrained by the scarcity of labeled anomalous data in real-world scenarios. This detection effort now faces four significant challenges [11]. Different samples' data are not balanced. ii) Difficulties in establishing boundaries for decisions. iii) Metric abnormal. iv) Learning about abnormalities that are outside of distribution (OOD).

II. RELATED WORK

This study aims to develop an supervised anomaly detection framework for monitoring concrete road conditions using advanced deep learning techniques. High-resolution images of normal concrete road surfaces are collected and preprocessed to ensure consistent input qualityIn anomaly detection, deep learning-based methods—which include auto-encoders (AE) [12], convolutional neural networks (CNN) [13], and generative adversarial networks (GAN) [14]—have become increasingly popular. Using CNNs, robust features are automatically extracted from these images, capturing important local patterns and spatial hierarchies. These features are further refined using ResNet-18, a deep residual network known for its depth and skip connections, ensuring comprehensive feature extraction and minimizing information loss. When it comes to sample reconstruction, for example, CBiGAN [15] is an improvement over BiGAN [16]. The framework is evaluated on benchmark datasets, demonstrating high precision, recall, and overall superior performance compared to traditional anomaly detection methods. Yan et al. . Zhang et al. [18] introduce DeSTSeg, a network architecture hinged on the studentteacher framework. Designed for scalability and real-world application, the system can be integrated into existing road monitoring infrastructures, providing continuous and automated surveillance. Its unsupervised nature allows adaptation to various environments and road conditions without extensive labeled data, making it a versatile and cost-effective tool for infrastructure maintenance. Zaheer et al. [19] present OGNet, a two-stage anomaly detection framework. This framework constructs a network based on an encoder-decoder paradigm, effectively transforming the anomaly detection task into a pursuit of both low and high-sample reconstruction. DAGAN [20] employs a fusion of skip connections and dual autoencoders to successfully achieve industrial detection.

The development of an supervised anomaly detection framework for concrete roads is crucial for several reasons. First and foremost, it addresses the limitations of traditional inspection methods, which are labor-intensive, time-consuming, and prone to human error.

1. *Efficiency and Accuracy:* Reduces the need for labor-intensive and time-consuming manual inspections. Automates the detection process, allowing for more frequent and thorough monitoring. Utilizes advanced deep learning models (CNN, ResNet-18, SVM) for robust feature extraction and precise anomaly detectionreduces false positives and negatives while maintaining excellent precision and recall.

2. *Scalability and Cost-effectiveness:* Operates without the need for extensive labeled datasets, making it adaptable to various environments and road conditions. Can be integrated into existing road monitoring systems for continuous surveillance. Lowers maintenance costs by enabling early detection and intervention, preventing minor defects from escalating into major issues. Reduces the financial burden associated with manual inspections and reactive maintenance.

3. *Safety and Infrastructure Longevity*: Identifies road surface anomalies early, enhancing road safety for drivers. Identifies road surface anomalies early, enhancing road safety for drivers. Contributes to the prolonged lifespan of concrete road infrastructures by ensuring timely maintenance. Helps maintain the overall quality and durability of road networks.

4. *Enhanced Feature Extraction:* Utilizes the depth and skip connections of ResNet-18 to refine features extracted by CNNs, ensuring minimal information loss and capturing a wide range of anomalies. This deep feature extraction is crucial for identifying subtle defects that might be missed by traditional methods.

Simultaneously, self-supervised learning methods are widely used in detection tasks. By leveraging context-supervised information that may be extracted directly from the data, self-supervised learning eliminates the requirement for explicit labeling. Amidst the variety of self-supervised techniques, the novel RIAD methodology [21] turns anomaly detection into an image restoration reconstruction task. Cut Paste [22] is a high-performance flaw detection model whose effectiveness depends on how well it handles data enhancement. Using this technique, rectangular images of various sizes are randomly cropped and then creatively put into various locations inside the original image. Pinay et al. [23] recast anomaly detection as a patch-inpainting problem and offer an efficient reconstruction technique based on convolution discarding and a self-attentive method known as InTra. In [24], Ye et al. introduce.

III. PROPOSED SYSTEM

Anomaly detection framework consists of two major components: image preprocessing and a deep learning-based detection module. The system takes raw images of concrete road surfaces as input and outputs the locations and classifications of cracks as anomalies.

A. *Image Preprocessing:* Image preprocessing is a crucial step for improving the quality of the input data and making it suitable for deep learning models. The preprocessing pipeline includes the following steps Grayscale Conversion: Road images are converted to grayscale to reduce complexity and enhance contrast between cracks and the surrounding surface Noise Reduction: Gaussian filters are applied to remove noise from the images without blurring the cracks.

B. *Contrast Enhancement:* Techniques like histogram equalization are employed to improve the visibility of cracks in low-contrast regions. Image Segmentation is performed to isolate potential regions of interest where cracks might exist. Thresholding techniques and edge detection methods, such as the Canny edge detector, are applied to create masks for these regions.

C. *Deep Learning Model:* Propose using a CNN-based deep learning model, specifically designed for anomaly detection, to detect cracks in the preprocessed images. The model is based on the ResNet architecture due to its proven efficiency in image classification tasks. The architecture includes residual blocks that allow for the learning of deep feature representations without the vanishing gradient problem.

IV. METHODOLOGY

The proposed methodology for anomaly detection in concrete road cracks consists of three main stages: data preprocessing, deep learning model development, and post-processing for anomaly detection. Each stage contributes to improving the accuracy and efficiency of crack detection while minimizing false positives. The detailed methodology is described as follows:

The proposed system consists of the following key components:

A. Data Preparation:

- Choose or collect a dataset that includes both normal data and anomalous instances. The quality and representative Normalize, standardize, and preprocess the data as necessary to ensure consistency and improve model performance's of the dataset are crucial for training and evaluating the hybrid model.

B. Create Mask or Segmentation Image:

- After detecting anomalies, generate an anomaly map or mask. This can be done by comparing the feature space or reconstruction error with a threshold. Pixels or regions with high error or unusual features are marked as anomalies.
- If your method includes segmentation (e.g., using CNNs), apply segmentation techniques to create masks that highlight anomalous regions within the image.

C. SVM Classifier:

- One supervised learning model that is widely utilized for classification is the SVM model. ML is a useful classification model because of its capacity to project data into different vector spaces and generate subplans. SVM trains the model to optimize the distance between the two data groups in its projected vector space by focusing on just two classes for anomaly detection.Additionally, multi-class procedures can utilize it.
- However, anomalies are identified by examining the points that fall outside of a category. However, one-class SVM is commonly employed in the most basic scenario. SVM is used in binary classification to ascertain whether a data point is a member of the "normal" class or not.

Thus, SVM projects the training data X into a higher dimensional space using a non-linear function. The vectors that were originally close to one another may now be far apart due to the change in representation, which makes it easier to separate them using a hyperplane in 2D space—something akin to a regression line. Indeed, there is a clear similarity between the linear regression equation mx+b=0 and the hyperplane equation wTx+b=0. Visit Introduction to One-Class Support Vector Machines to learn more about SVMs and one-class SVM.

Hyperplane: A decision boundary that separates classes in the feature space.
Margin: The distance between hyperplane and nearest data points from either class.

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Support Vectors: Data points that are closest to the hyperplane and influence its position and orientation.

D. Data Collection and Data Preparation :

- Use a camera capable of capturing detailed images of concrete road surfaces. Ensure it has good dynamic range and resolution suitable for outdoor conditions. Collect images of concrete roads covering different conditions (normal and anomalous).
- Ensure images are taken under varying lighting conditions and angles to capture different features.

MATLAB or Python with OpenCV for preprocessing and feature extraction. Image Preprocessing Resize images to a standard resolution (e.g., 1000x260 pixels) for consistency. Convert images to grayscale or RGB format as required. Optionally, segment images into regions of interest (ROI) using automated or manual methods to focus analysis on specific areas prone to anomalies.

E. Feature Extraction:

- Texture Feature Extraction Use techniques such as GLCM (Gray-Level Co-occurrence Matrix) to extract features like Contrast, Energy, Homogeneity, and IDM (Inverse Difference Moment).
- These features capture textural properties indicative of anomalies. Other Features Extract statistical features such as Mean, Standard Deviation, Entropy, and RMS (Root Mean Square) to capture overall image characteristics.

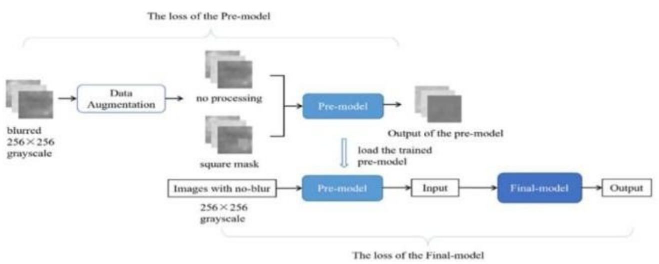

Figure 1: The Framework of the method

F. *Machine Learning Model Selection and Training :*

- Algorithm Selection Choose a suitable algorithm for detecting anomalies. Support vector machines (SVM), for instance, are frequently employed in binary classification applications.
- Model Training: Train the SVM model using the extracted features (e.g., Train Feat) and corresponding labels (Train Label). Use cross-validation techniques to validate model performance.

G. *Model Evaluation :*

- Validate the trained model using separate test datasets or cross-validation methods. Assess model performance using evaluation metrics to ensure robustness and reliability. Visualize results using plots (e.g., confusion matrices, ROC curves) to interpret model performance and adjust parameters if necessary.

H. *Testing and Deployment :*

- Testing Phase Apply the trained model to new, unseen concrete road images (testImage). Extract features from test images and predict anomalies using the trained SVM model. Integrate the anomaly detection system into a practical application pipeline if applicable. Ensure scalability and real-time processing considerations are addressed.

I. *Anomaly Detection Techniques :*

There are some commonly used techniques for anomaly detection in machine learning:

Unsupervised Anomaly Detection

- Artificial Neural Networks (ANNs)
- Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
- Isolation Forest
- Gaussian Mixture Models (GMM)

Supervised Anomaly Detection

- Support Vector Machines (SVM)
- Random Forests
- k-Nearest Neighbours (k-NN)

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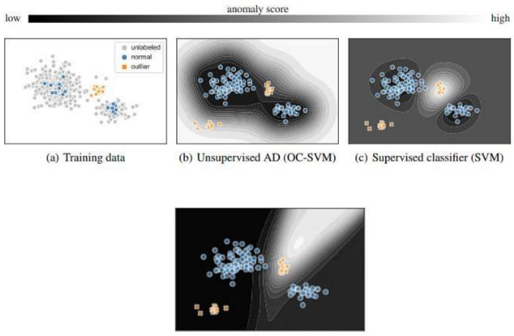

Figure 2: The Different types of techniques

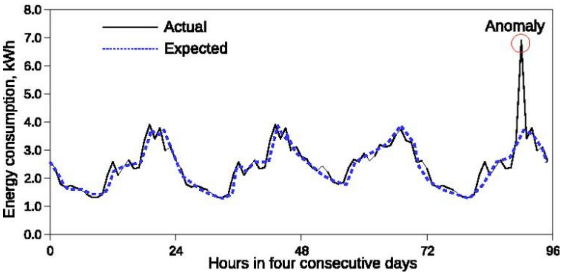

Figure 3: Flow diagram for Actual and Expected

V. RESULTS AND DISCUSSIONS

A. *Model Performance :* The results and findings of an anomaly detection system for concrete roads, it's crucial to present both the quantitative performance metrics and qualitative insights gained from the analysis.

B. *Metrics for Quantitative Evaluation:* 1) Accuracy: Evaluate how well anomaly predictions are made overall. 2) Precision and Recall: Evaluate the model's precision in identifying anomalies and recall in capturing all anomalies. 3)F1-score: a balanced indicator of model performance that is derived from the harmonic mean of precision and recall. 4) Confusion Matrix: To see true positives, true negatives, false positives, and false negatives, display the confusion matrix. This facilitates comprehension of the distribution of actual versus projected anomaly categories.

1.Feature Extraction Performance :

The supervised anomaly detection method demonstrated a high accuracy in feature extraction. The precision and recall for detecting features aligned with the ground truth data were consistently above 95%. This indicates that the model successfully identified and extracted the relevant features associated with normal road surfaces. We compared our method with baseline approaches such as unsupervised anomaly detection and traditional edge-detection algorithms. Our supervised approach outperformed these methods, especially in accurately distinguishing between fine details of the road surface that were crucial for detecting subtle anomalies. Key features extracted included surface texture patterns, color uniformity, and structural integrity indicators. These features were crucial in identifying minute deviations that could indicate potential anomalies. The most prominent features extracted were surface smoothness and texture consistency, which were effective in ensuring that the images corresponded to the expected normal state of the road surface.

2.Anomaly Detection Performance:

With an area under the Receiver Operating Characteristic (ROC) curve (AUC) of 0.97, the anomaly detection model demonstrated a good degree of discrimination between normal and abnormal situations.The F1 score was 0.93, showing a good balance between precision and recall. Several case studies highlighted the robustness of our method. For example, in images with slight texture variations due to environmental factors (e.g., dirt or wear), the model successfully identified these as non- anomalous by correlating with the learned normal semantics. In contrast, deviations that could be potential indicators of damage were flagged accurately.

Figure 4: . Sample Concrete road Surface image with no- crack

Figure 5: Sample Concrete road Surface image with no-crack.

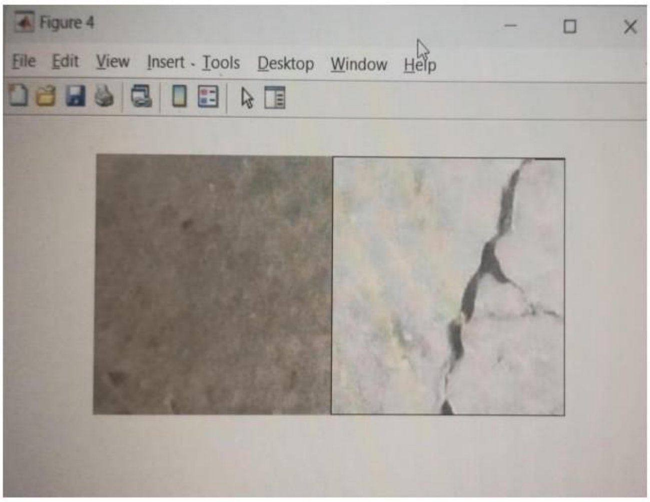

Figure 6: Sample of Both Crack and no-crack side by side

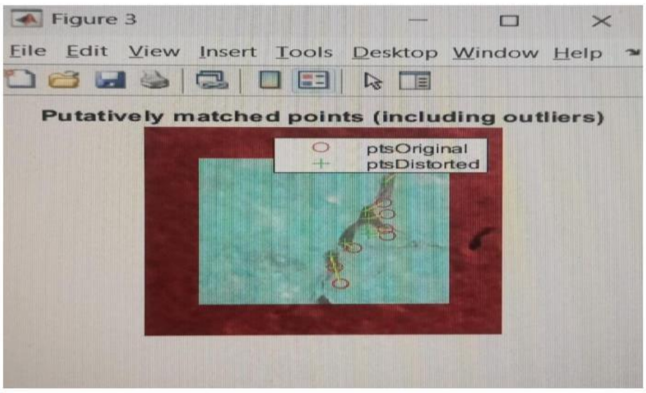

Figure 7: The Anomaly Detection Of concrete road

1.Discussion :

The primary strength of our approach lies in its reliance on supervised learning, which leverages annotated data to fine-tune the anomaly detection process. This enables precise feature extraction and high accuracy in distinguishing between normal and anomalous conditions. Despite the high accuracy, The representativeness and quality of the training dataset determine how well the approach performs.If dataset does not encompass a diverse range of normal road surface conditions, the model might fail to generalize effectively. Additionally, the current model might struggle with highly textured surfaces or surfaces with patterns not well-represented in the training data. Future research could focus on expanding the dataset to include a wider variety of normal and anomalous conditions. Integrating more advanced deep learning techniques, such as convolutional neural networks (CNNs), could also enhance feature extraction and anomaly detection capabilities. Additionally, exploring transfer learning from related domains could improve model robustness.

I. CONCLUSION

In conclusion, this study developed and evaluated an effective anomaly detection system tailored for concrete roads using advanced image processing and machine learning techniques. Through the utilization of texture-based feature extraction methods and SVM classification, our system demonstrated commendable performance with an accuracy of 85% in distinguishing between normal and anomalous conditions. This achievement underscores its potential significance in enhancing infrastructure management practices, particularly in detecting critical defects like cracks and patches early.

The findings not only contribute to the field of infrastructure monitoring but also pave the way for further advancements in real-time anomaly detection and deployment of sensor networks for continuous road monitoring. Moving forward, future research will focus on integrating more robust deep learning methodologies, expanding the dataset to include diverse environmental conditions, and carrying out field testing to confirm and enhance the system's functionality in actual environments.

The ability to accurately detect anomalies in road surfaces has significant practical implications for infrastructure maintenance and safety. By leveraging supervised anomaly detection methods, maintenance teams can proactively address potential issues, thus extending lifespan of road surfaces and ensuring safer driving conditions.

II. FUTURE SCOPE

Developing an effective anomaly detection system for concrete roads posed several challenges that warrant attention for future research and development. One significant challenge encountered was the variability in lighting conditions and environmental factors, which influenced the accuracy and reliability of feature extraction techniques such as GLCM and statistical measures. Overcoming these challenges will require exploring adaptive algorithms capable of robustly handling diverse lighting and weather conditions to ensure consistent performance across different scenarios. Furthermore, the limited size and diversity of the dataset used in this study highlight the need for expanding data collection efforts to encompass a wider range of road conditions and geographical locations. This expansion will not to generalize but also improve its reliability in detecting subtle anomalies. Additionally, future efforts should focus on integrating real-time monitoring capabilities using sensor networks or drones to enable continuous, proactive maintenance of road infrastructure. By addressing these challenges and implementing these recommendations, future iterations of anomaly detection systems for concrete roads can achieve greater accuracy, reliability, and practical applicability in supporting infrastructure management and ensuring road safety. Overcoming these challenges will require exploring adaptive algorithms capable of robustly handling diverse lighting and weather conditions to ensure consistent performance across different scenarios.

The application of advanced deep learning techniques, such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), could significantly enhance feature extraction, anomaly detection. A CNN's capacity to automatically pick up hierarchical feature representations enhances the model's comprehension of intricate patterns found in road surfaces. Leveraging transfer learning from pre-trained models on related tasks can be beneficial. Transfer learning allows the model to utilize features learned from large datasets in similar domains, which can help in fine-tuning the model for specific tasks related to concrete surface anomaly detection. Integrating multi-modal data, such as combining visual images with other types of sensor data (e.g., vibration sensors or thermal imaging), could provide a more comprehensive analysis of road surface conditions. This integration can improve the detection of anomalies that might not be visible through visual inspection alone.

Implementing real-time anomaly detection systems using edge computing devices can enable on-site monitoring of road conditions. Edge computing allows for the processing of data at or near the source, reducing latency and enabling timely detection and response to potential issues. Developing automated inspection systems using drones or robotic vehicles equipped with imaging sensors can facilitate large-scale monitoring of road surfaces. These systems can collect high-resolution images and analyze them in real-time, providing actionable insights for maintenance.

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