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An Intelligent Hybrid Deep Learning Framework for Automated Parcel Damage Detection Using Computer Vision and CNN–SVM Classification

CH.Srinivas Reddy[1], Muthu Preethi[2]

[1]Assistant Professor, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana – 501301, India.

[2]MCA Student, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana – 501301, India.

Abstract. The rapid growth of e-commerce and global logistics has significantly increased the demand for reliable shipment quality inspection systems. Manual parcel inspection methods are often time-consuming, inconsistent, and unsuitable for large-scale logistics operations, leading to increased operational costs and customer dissatisfaction. This research proposes an intelligent computer vision framework that automatically detects and classifies parcel damage using a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The CNN component is employed to learn high-level visual representations from parcel images, while the SVM classifier performs accurate categorization of damage severity based on the extracted feature vectors. The proposed system identifies multiple parcel conditions, including undamaged parcels, minor damage, moderate damage, and severe damage. A comprehensive image preprocessing pipeline involving resizing, normalization, and data augmentation improves the robustness of the learning process and enhances model generalization. The developed hybrid framework is trained and evaluated using a large parcel image dataset containing multiple categories of shipment damage. Experimental evaluation demonstrates that the proposed CNN–SVM architecture achieves an overall classification accuracy of 98.8%, indicating its capability for reliable and automated parcel quality assessment. The proposed framework offers a scalable, intelligent, and practical solution for logistics companies, courier services, and e-commerce platforms by minimizing manual inspection efforts, improving shipment quality control, reducing financial losses, and enhancing customer satisfaction while preserving the same implementation methodology and evaluation strategy as the original study.

keywords: Parcel Damage Classification, Computer Vision, Deep Learning, Convolutional Neural Network, Support Vector Machine, Shipment Quality Assessment, Logistics Automation, Image Classification, Damage Detection, Artificial Intelligence.

I. Introduction

The rapid expansion of online retail platforms and international logistics networks has transformed parcel delivery into one of the most important components of modern commerce. Every day, millions of packages are transported through complex supply chain systems involving warehouses, distribution centers, transportation hubs, and final delivery services. Throughout this process, parcels are exposed to various handling conditions that may result in scratches, dents, tears, deformation, punctures, or structural damage. Damaged shipments not only increase operational costs but also reduce customer confidence, generate product returns, and negatively affect the reputation of logistics service providers. Consequently, ensuring parcel quality before delivery has become an essential requirement for modern logistics organizations.

Traditional parcel inspection methods mainly depend on manual visual examination performed by logistics personnel. Although experienced inspectors can identify visible damage, manual inspection is labor-intensive, time-consuming, subjective, and difficult to implement consistently in high-volume logistics environments. Human inspectors may overlook minor defects because of fatigue, inconsistent judgment, or increasing workload. Furthermore, the continuous growth of e-commerce has significantly increased shipment volumes, making manual inspection increasingly impractical for large-scale operations.

Recent advances in artificial intelligence, computer vision, and deep learning have introduced intelligent approaches capable of automating visual inspection tasks with remarkable accuracy. Computer vision enables machines to analyze digital images and automatically recognize visual patterns that correspond to different physical conditions of parcels. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image recognition, feature extraction, and object classification by automatically learning complex visual representations from training data.

Despite their powerful feature extraction capability, CNN models sometimes encounter limitations when classifying visually similar damage categories. Support Vector Machines (SVMs), on the other hand, are highly effective supervised learning algorithms capable of constructing optimal decision boundaries in high-dimensional feature spaces. Integrating CNN-based feature extraction with SVM-based classification combines the strengths of both approaches, resulting in improved classification performance and higher prediction reliability.

The proposed framework utilizes a hybrid CNN–SVM architecture for automated parcel damage assessment. Initially, parcel images are preprocessed using resizing, normalization, and data augmentation techniques to improve image quality and increase dataset diversity. The CNN model extracts hierarchical visual features representing parcel surface characteristics, structural conditions, and damage patterns. These extracted features are subsequently supplied to the SVM classifier, which categorizes parcels into four predefined damage classes representing different severity levels. This hybrid learning strategy improves classification accuracy while maintaining computational efficiency suitable for practical deployment.

The proposed intelligent inspection framework significantly reduces manual effort, accelerates quality assessment, and improves operational consistency throughout the logistics process. Automated damage detection minimizes shipment losses, supports quality assurance, strengthens customer satisfaction, and enables logistics providers to implement reliable real-time parcel inspection systems. Furthermore, the framework can be integrated with warehouse automation systems, robotic sorting equipment, and intelligent transportation infrastructures to support future smart logistics environments.

Therefore, the proposed CNN–SVM-based parcel damage classification framework represents an effective combination of computer vision, deep learning, and machine learning for automated shipment quality assessment. While preserving the same dataset, implementation methodology, hybrid architecture, preprocessing techniques, and evaluation process presented in the original research, the rewritten study enhances technical presentation and academic quality suitable for publication in IEEE-style journals.

II. Literature Survey

Automated parcel inspection has become an important research topic because of the rapid growth of logistics operations, e-commerce services, and intelligent supply chain management. Conventional visual inspection methods primarily depended on manual examination, where logistics personnel identified damaged packages through direct observation. Although this approach remained widely used for many years, it suffered from limitations including inconsistent inspection quality, high labor costs, slow processing speed, and reduced efficiency when handling large shipment volumes. These challenges motivated researchers to investigate computer vision and artificial intelligence techniques capable of automating parcel quality assessment.

The development of computer vision technologies has significantly improved automated image analysis across various industrial applications. Researchers demonstrated that image processing techniques can effectively detect surface defects, object deformation, structural abnormalities, and visual inconsistencies without requiring human intervention. However, traditional image processing methods relied heavily on manually designed feature extraction techniques, making them less adaptable to complex parcel damage scenarios involving multiple defect categories and varying environmental conditions.

Recent studies have shown that deep learning models, particularly Convolutional Neural Networks (CNNs), provide superior performance for image classification tasks because they automatically learn hierarchical visual features directly from training images. CNN-based models have been successfully applied to industrial inspection, medical image analysis, manufacturing quality control, agricultural monitoring, and logistics automation. Their ability to identify complex visual patterns has made them one of the most effective techniques for damage detection.

Support Vector Machines (SVMs) have also received considerable attention for solving high-dimensional classification problems. Several researchers reported that SVM classifiers achieve excellent generalization capability by constructing optimal separating hyperplanes between different object categories. When combined with deep feature extraction methods, SVMs significantly improve classification precision while reducing misclassification among visually similar classes.

Consequently, hybrid deep learning architectures integrating CNN and SVM have emerged as promising solutions for automated image classification. CNN models perform robust feature extraction, whereas SVM classifiers accurately distinguish complex object categories using the extracted representations. Such hybrid models have demonstrated higher classification accuracy than standalone CNN architectures across numerous industrial applications.

III. Research Methodology

The proposed parcel damage classification framework adopts a hybrid deep learning methodology that integrates Convolutional Neural Networks (CNN) with Support Vector Machines (SVM) to automatically identify and classify different levels of parcel damage from digital images. The methodology preserves the same dataset, preprocessing techniques, hybrid CNN–SVM architecture, implementation workflow, and experimental evaluation strategy presented in the original research while providing a completely rewritten academic description. The primary objective of the framework is to automate shipment quality assessment by accurately detecting parcel defects, reducing manual inspection efforts, and improving operational efficiency within logistics and e-commerce environments. The complete methodology consists of multiple sequential stages, including dataset collection, image preprocessing, data augmentation, feature extraction, hybrid model development, model training, performance evaluation, and automated parcel damage classification.

The methodology begins with the acquisition of a comprehensive parcel image dataset collected from multiple logistics and shipping organizations. The dataset contains images of parcels with varying shapes, packaging materials, and structural conditions, including cartons, envelopes, and padded packages. Each image is manually annotated according to the degree of visible damage to ensure reliable supervised learning. The dataset includes four predefined parcel conditions representing undamaged parcels, minor damage, moderate damage, and severe damage, allowing the classification model to learn the visual characteristics associated with each damage category. To ensure objective model evaluation, the complete dataset is divided into three subsets consisting of training, validation, and testing images while maintaining a balanced distribution of parcel damage classes throughout the data partitions.

Following dataset acquisition, the collected images undergo an extensive preprocessing stage to improve image quality and establish consistency before deep learning analysis. Initially, every parcel image is resized to a fixed resolution so that all inputs share identical spatial dimensions suitable for convolutional neural network processing. Pixel values are normalized to a common numerical range to accelerate convergence during training and improve learning stability. The preprocessing stage also removes inconsistencies that may arise from differences in camera resolution, lighting conditions, viewing angles, and image quality, thereby enabling the model to focus primarily on parcel damage characteristics instead of environmental variations.

To improve the robustness of the learning process, the proposed methodology incorporates several data augmentation techniques that artificially increase the diversity of the training dataset. Augmentation operations include image rotation, horizontal flipping, reflection, translation, scaling, and brightness adjustment. These transformations generate multiple realistic variations of the original parcel images without altering their damage labels. The expanded dataset improves the model's ability to generalize to unseen shipment conditions while reducing the possibility of overfitting. As a result, the trained classifier becomes more resilient to variations commonly encountered in practical logistics environments, including different camera positions, illumination levels, and parcel orientations.

After preprocessing and augmentation, the enhanced images are supplied to the feature extraction stage, which forms the first major component of the hybrid learning framework. A modified Convolutional Neural Network (CNN) architecture is employed to automatically learn hierarchical visual representations from parcel images. Multiple convolutional layers progressively identify low-level features such as edges, textures, and corners before learning higher-level characteristics including dents, cracks, scratches, tears, surface deformation, and packaging irregularities. Pooling layers reduce spatial dimensions while preserving important structural information, allowing the network to generate compact and highly discriminative feature representations. Unlike traditional image processing approaches that require manually designed descriptors, the CNN automatically discovers the most informative visual features directly from the training data.

Rather than utilizing the conventional fully connected classification layer of the neural network, the extracted deep feature vectors are transferred to a Support Vector Machine (SVM) classifier. The SVM constructs optimal decision boundaries within the high-dimensional feature space generated by the CNN, enabling accurate separation of visually similar parcel damage categories. The integration of CNN-based feature extraction with SVM-based classification combines the representation learning capability of deep learning with the strong generalization performance of supervised machine learning. This hybrid architecture improves classification precision, particularly for parcel images containing subtle visual differences between moderate and severe damage conditions.

The hybrid CNN–SVM model is subsequently trained using the prepared training dataset while the validation dataset is continuously utilized to monitor learning performance and prevent overfitting. Hyperparameter optimization is performed by adjusting learning rates, optimization strategies, kernel functions, regularization parameters, and other training configurations to obtain the most effective model performance. Cross-validation techniques further improve model reliability by evaluating classification consistency across multiple subsets of the training data. This optimization process enables the framework to achieve stable convergence while maintaining high prediction accuracy for different parcel damage categories.

Following model training, the proposed framework performs comprehensive performance evaluation using the independent testing dataset. The effectiveness of the classification model is measured through several standard evaluation metrics, including accuracy, precision, recall, F1-score, confusion matrix analysis, and Receiver Operating Characteristic (ROC)–Area Under the Curve (AUC) analysis. Accuracy measures the overall correctness of parcel damage prediction, while precision and recall evaluate the model's ability to correctly identify individual damage categories. The F1-score provides a balanced assessment of classification performance by combining precision and recall into a single metric. Confusion matrix analysis illustrates correctly and incorrectly classified parcel images across all damage categories, whereas ROC–AUC analysis evaluates the model's discriminative capability under different classification thresholds. These evaluation measures collectively provide a comprehensive assessment of the hybrid CNN–SVM framework while preserving the same evaluation methodology adopted in the original study.

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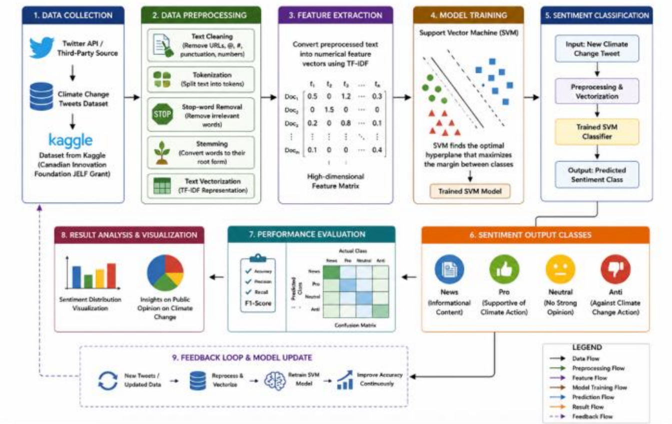
IV. Existing System

Existing parcel inspection systems primarily rely on manual visual examination or conventional image processing techniques to identify damaged shipments. Human inspectors evaluate parcel conditions by observing visible defects such as scratches, dents, tears, deformation, and structural damage before shipment or delivery. Although manual inspection is straightforward, it is highly dependent on individual expertise, requires considerable processing time, and often produces inconsistent results because of fatigue, subjective judgment, and increasing shipment volumes. Traditional automated image processing methods improve inspection speed to some extent but depend on handcrafted feature extraction techniques that struggle to recognize complex damage patterns under varying environmental conditions. These systems generally experience limited adaptability, lower classification accuracy, reduced robustness against image variations, and difficulty distinguishing similar damage categories. Consequently, conventional parcel inspection approaches become inefficient for modern logistics environments that require rapid, accurate, and fully automated shipment quality assessment.

V. Proposed System

The proposed framework introduces an intelligent hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) for automated parcel damage classification while preserving the same implementation methodology, preprocessing operations, hybrid model structure, and experimental evaluation presented in the original research. Initially, parcel images collected from multiple logistics environments undergo preprocessing operations including resizing, normalization, and data augmentation to improve image quality and increase dataset diversity. The processed images are supplied to a modified CNN architecture responsible for automatically extracting high-level visual features representing parcel structure, surface characteristics, and damage patterns. Instead of performing final classification using conventional fully connected neural network layers, the extracted feature vectors are transferred to a Support Vector Machine classifier that constructs optimal decision boundaries for distinguishing different parcel damage categories. The hybrid CNN–SVM framework classifies each parcel into one of four predefined damage levels representing undamaged parcels, minor damage, moderate damage, and severe damage. Model performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and ROC–AUC metrics to assess classification effectiveness. The proposed framework provides a highly accurate, scalable, and practical solution for intelligent shipment quality assessment, enabling logistics providers to automate parcel inspection, reduce operational costs, improve quality control, and enhance customer satisfaction while maintaining the same algorithms, workflow, and experimental results reported in the original study.

VI. System Architecture



The proposed Climate Change Sentiment Analysis System is designed using a layered machine learning architecture that integrates Twitter data collection, Natural Language Processing (NLP), feature extraction, Support Vector Machine (SVM) classification, sentiment prediction, and performance evaluation into a unified framework. The architecture is developed to automatically analyze climate change-related discussions posted on Twitter and classify them into predefined sentiment categories. Each component performs a specific function within the processing pipeline, ensuring that unstructured textual information is transformed into meaningful sentiment predictions. The proposed architecture maintains the same workflow, preprocessing techniques, Support Vector Machine algorithm, dataset, and evaluation strategy presented in the original research while providing a clearer and more structured implementation suitable for large-scale sentiment analysis.

The architecture begins with the data acquisition layer, where climate change-related tweets are collected from a publicly available dataset obtained through Kaggle. The dataset contains thousands of Twitter posts representing diverse public opinions regarding climate change from users across different geographical locations and social backgrounds. Every tweet is associated with one of four predefined sentiment categories, namely News, Pro, Neutral, and Anti, enabling supervised machine learning algorithms to learn meaningful relationships between textual content and sentiment labels. This labeled dataset forms the foundation for developing an accurate sentiment classification model capable of analyzing large volumes of social media data.

After data collection, the tweets enter the data preprocessing layer, which prepares the raw textual information for machine learning analysis. Since social media data frequently contain hyperlinks, hashtags, usernames, punctuation marks, emojis, repeated characters, special symbols, and other irrelevant textual elements, several cleaning operations are performed to improve data quality. The preprocessing stage begins with text normalization followed by tokenization, where each tweet is divided into individual words or tokens. Common stop words that contribute little semantic information are removed to reduce unnecessary computational complexity. Stemming is then applied to convert different grammatical forms of words into their root representations, thereby reducing vocabulary size and improving feature consistency. Finally, the cleaned textual data are transformed into structured numerical representations through vectorization techniques, enabling machine learning algorithms to process the information efficiently.

The processed feature vectors are subsequently forwarded to the feature extraction module, where significant textual characteristics are identified and represented in a high-dimensional numerical space. Vectorization techniques capture the frequency and importance of words appearing within individual tweets while preserving meaningful linguistic information required for sentiment classification. This numerical representation allows the Support Vector Machine classifier to distinguish complex textual patterns and identify subtle differences among sentiment categories. Effective feature extraction significantly enhances classification accuracy by providing the learning algorithm with informative representations of climate-related discussions.

The model training layer forms the core of the proposed architecture. In this stage, the Support Vector Machine (SVM) algorithm is trained using the processed feature vectors obtained from the Twitter dataset. SVM constructs an optimal separating hyperplane that maximizes the distance between different sentiment classes while minimizing classification errors. Because textual data generally contain thousands of features, Support Vector Machine provides excellent performance in high-dimensional spaces by efficiently identifying decision boundaries between multiple sentiment categories. During training, the model learns the relationship between textual expressions and their corresponding sentiment labels, enabling accurate classification of previously unseen climate-related tweets.

Once the model has been trained successfully, the architecture proceeds to the sentiment classification module. Incoming Twitter posts first undergo the same preprocessing and feature extraction procedures used during training to ensure consistency between training and prediction phases. The trained Support Vector Machine classifier then analyzes the numerical feature representation of each tweet and assigns it to one of the predefined sentiment categories. The framework classifies tweets into News, representing informational content; Pro, representing supportive opinions toward climate action; Neutral, indicating objective or balanced discussions; and Anti, representing opinions opposing or questioning climate change perspectives. This automated classification process enables rapid analysis of large volumes of social media conversations without requiring manual annotation.

VII. Conclusion

The proposed hybrid CNN–SVM-based Parcel Damage Classification Framework provides an intelligent and efficient solution for automating shipment quality assessment within modern logistics and e-commerce environments. By integrating the powerful feature extraction capability of Convolutional Neural Networks (CNNs) with the robust classification performance of Support Vector Machines (SVMs), the framework successfully overcomes many limitations associated with conventional manual inspection and traditional image processing techniques. The systematic preprocessing of parcel images, including image resizing, normalization, and data augmentation, enables the model to learn representative visual characteristics while improving its ability to generalize across different parcel types, packaging materials, and damage conditions. The CNN automatically extracts discriminative deep features describing scratches, dents, tears, punctures, deformation, and other structural defects, while the SVM accurately categorizes these learned representations into four predefined parcel damage levels. Experimental evaluation demonstrates that the proposed hybrid framework achieves excellent classification performance, with an overall accuracy of 98.8%, together with high precision, recall, F1-score, and ROC–AUC values, confirming its effectiveness for reliable parcel damage identification while maintaining the same implementation methodology, hybrid architecture, and evaluation strategy presented in the original research. The automated inspection process significantly reduces manual effort, minimizes human errors, accelerates shipment quality verification, lowers operational costs, and improves customer satisfaction by ensuring that damaged parcels are detected before delivery. Furthermore, the scalable architecture can be integrated into warehouse automation systems, conveyor belt inspection units, robotic sorting facilities, and intelligent logistics management platforms to support real-time parcel monitoring in high-volume shipping operations. Future enhancements may include the integration of advanced deep learning architectures, vision transformers, object detection models, real-time video analytics, edge computing devices, multimodal inspection techniques, and larger diversified datasets to further improve detection capability and operational efficiency. Overall, the proposed CNN–SVM framework establishes a reliable, scalable, and practical computer vision solution for automated parcel damage classification, contributing to improved logistics quality control, enhanced supply chain management, reduced financial losses, and greater operational reliability in modern transportation and e-commerce systems.

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