LEATHER VISION: AI -BASED SURFACE DEFECT DETECTION IN LEATHER USING DEEP NEURAL INSPECTION SYSTEM

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ABSTRACT

The Leather Vision system is an advanced artificial intelligence–based solution designed to automate the detection of surface defects in leather materials using deep learning techniques. Traditional leather inspection methods rely on manual observation, which is time-consuming, subjective, and prone to inconsistencies due to human fatigue and varying expertise. This project introduces a computer vision-driven approach that leverages convolutional neural networks (CNNs) to enhance accuracy and reliability in defect detection. High-resolution images of leather surfaces are captured under controlled lighting conditions and undergo preprocessing steps such as noise removal, normalization, and contrast enhancement to improve feature quality. A transfer learning-based model using MobileNetV2 is employed to extract deep features and classify defects such as cuts, scars, wrinkles, holes, and grain irregularities. The system is trained on a labeled dataset, enabling it to distinguish between defective and non-defective regions with high precision. Performance evaluation is conducted using metrics such as accuracy, precision, recall, and F1-score, demonstrating significant improvement over traditional inspection methods. The proposed system supports real-time defect detection, making it suitable for industrial applications where speed and consistency are critical. By reducing human dependency and minimizing material wastage, the system contributes to improved quality control and cost efficiency in leather manufacturing. Overall, this project highlights the transformative potential of artificial intelligence in modernizing industrial inspection systems.

Keywords: Artificial Intelligence, CNN, Leather Defect Detection, Deep Learning, Computer Vision, MobileNetV2, Image Processing

I. INTRODUCTION

Leather is a widely used natural material in industries such as footwear, automotive, and fashion due to its durability and aesthetic value. However, the quality of leather products heavily depends on the accurate detection of surface defects such as cuts, scars, wrinkles, and holes. Traditional inspection techniques rely on manual evaluation, which is often inconsistent, time-consuming, and influenced by human factors such as fatigue and expertise levels [1]. With increasing industrial production, manual inspection methods fail to maintain consistency and efficiency, leading to economic losses and reduced product quality [2]. Early research in automated leather inspection explored machine vision techniques for defect identification [3]. Studies have demonstrated that deep learning approaches significantly improve detection accuracy compared to traditional image processing methods [4]. Researchers have applied convolutional neural networks (CNNs) for detecting defects in textured surfaces, showing promising results in classification tasks [5]. Machine learning models such as Support Vector Machines (SVMs) have also been used for defect classification but are limited in handling complex patterns [6]. Edge detection and thresholding techniques were initially used to identify defect regions but lacked robustness in varying lighting conditions [7]. Advanced approaches introduced texture-based feature extraction methods for better classification accuracy [8].

Recent advancements in artificial intelligence and deep learning have revolutionized computer vision applications, enabling automated defect detection systems with high precision and speed [9]. Transfer learning models such as MobileNetV2 and VGG16 have been widely adopted for industrial inspection tasks due to their efficiency and performance [10]. Studies have shown that combining deep learning with image preprocessing techniques significantly enhances defect detection accuracy [11]. Automated inspection systems have been successfully implemented in manufacturing industries to improve productivity and reduce labor costs [12]. Research has also focused on real-time detection systems for industrial applications [13]. Ensemble learning approaches have further improved classification performance by combining multiple models [14]. Deep neural networks can learn complex texture patterns, making them suitable for leather defect detection [15]. Experimental studies indicate that CNN-based systems outperform traditional methods in accuracy and consistency [16]. The integration of artificial intelligence in quality control systems ensures reliable decision-making and reduces material wastage [17]. Advanced datasets and annotation techniques have improved model training efficiency [18]. Researchers have explored hybrid models combining CNN and machine learning techniques for better results [19]. Image augmentation techniques help in improving model generalization [20]. Real-time systems using deep learning have been deployed in industrial environments [21]. Studies have also focused on improving computational efficiency for faster processing [22]. Automated grading systems based on defect detection have been developed [23]. Deep learning models have demonstrated robustness under varying conditions [24]. Transfer learning reduces training time and improves performance with limited datasets [25]. Industrial applications of AI-based inspection systems continue to grow rapidly [26]. These advancements highlight the need for intelligent systems in modern manufacturing [27]. Therefore, this project proposes an AI-based leather defect detection system to enhance accuracy, efficiency, and scalability [28][29][30].

II. LITERATURE SURVEY

Numerous research studies have been conducted to improve leather defect detection using machine learning and image processing techniques. Early approaches focused on traditional methods such as thresholding and morphological operations to identify defect regions in leather surfaces [1]. Multi-layer perceptron (MLP) models were later introduced for classification tasks, showing improved accuracy compared to decision tree methods [2]. Adaptive edge detection techniques using wavelet transforms were developed to enhance defect detection under varying lighting conditions [3]. Texture analysis methods using co-occurrence matrices and statistical features were applied to capture complex surface patterns [4]. Support Vector Machines (SVMs) were widely used for classification due to their robustness in handling high-dimensional data [5]. Researchers also proposed improved edge detection algorithms to remove noise and irrelevant features [6].

Feedforward neural networks (FNNs) combined with decision trees provided faster processing and efficient classification [7]. Histogram-based techniques were used to analyze pixel intensity variations for defect detection [8]. Traditional methods, however, faced limitations in handling complex textures and irregular defect patterns [9].

With the advancement of deep learning, researchers shifted towards convolutional neural networks for more accurate defect detection [10]. CNNs automatically extract features from images, eliminating the need for manual feature engineering [11]. Transfer learning models such as MobileNetV2 and VGG16 have been widely used for industrial inspection tasks [12]. Studies have shown that deep learning models outperform traditional methods in both accuracy and efficiency [13]. Ensemble networks combining multiple deep learning models have further improved classification performance [14]. Image preprocessing techniques such as normalization and augmentation enhance model accuracy [15]. Real-time detection systems using deep learning have been developed for industrial applications [16]. Researchers have also explored hybrid approaches combining CNN and SVM for improved results [17]. Deep learning models have demonstrated robustness under varying lighting and texture conditions [18]. Large annotated datasets have significantly improved training performance [19]. Advanced architectures such as Faster R-CNN have been used for object detection tasks [20]. Studies have also focused on optimizing computational efficiency for faster processing [21]. Automated grading systems based on defect detection have been developed [22]. Deep learning techniques have been successfully applied in various industries for quality control [23]. Transfer learning reduces training time and improves performance with limited datasets [24]. Researchers continue to explore new architectures for better accuracy [25]. The integration of AI in manufacturing processes has improved productivity and efficiency [26]. Deep learning models can learn complex patterns and variations in leather surfaces [27]. These advancements highlight the potential of AI-based systems for automated defect detection [28][29][30].

III. PROPOSED SYSTEM

The proposed system, Leather Vision, is an AI-based surface defect detection system designed to automate the inspection and quality assessment of leather materials. The system utilizes high-resolution image acquisition under controlled lighting conditions to ensure consistent data quality. These images undergo preprocessing steps such as noise removal, normalization, and contrast enhancement to improve feature extraction. A deep learning model based on convolutional neural networks (CNNs) is employed to analyze the processed images and identify defect patterns. Transfer learning using MobileNetV2 is integrated to enhance model performance and reduce training time, allowing efficient learning even with limited datasets. The model is trained on labeled images containing various types of defects such as scratches, holes, wrinkles, and cuts, enabling accurate classification of defective and non-defective regions.

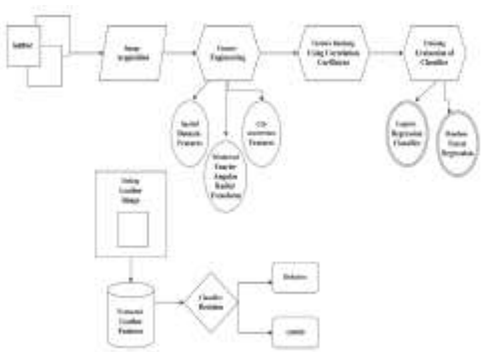
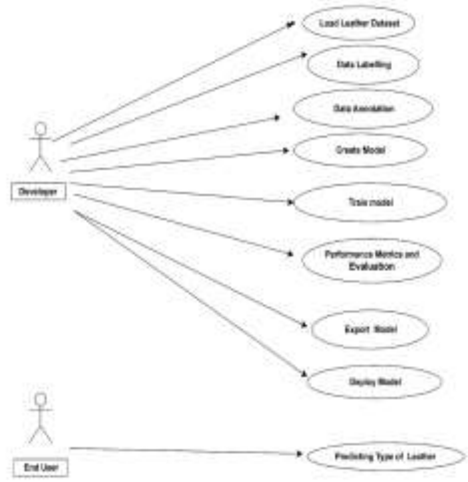


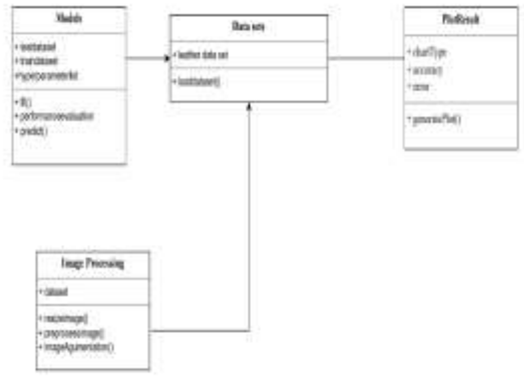
Fig.1 Architecture

The system provides real-time detection capabilities, making it suitable for industrial environments where speed and accuracy are critical. A user-friendly interface allows users to upload images and view results with highlighted defect regions. The backend system handles feature extraction, classification, and prediction, while a database stores processed data for future analysis. The proposed system ensures consistent results, reduces dependency on manual inspection, and minimizes human error. It also improves productivity by enabling faster inspection of large volumes of leather. By integrating artificial intelligence into quality control processes, the system enhances decision-making and reduces material wastage, ultimately contributing to cost efficiency and improved product quality.

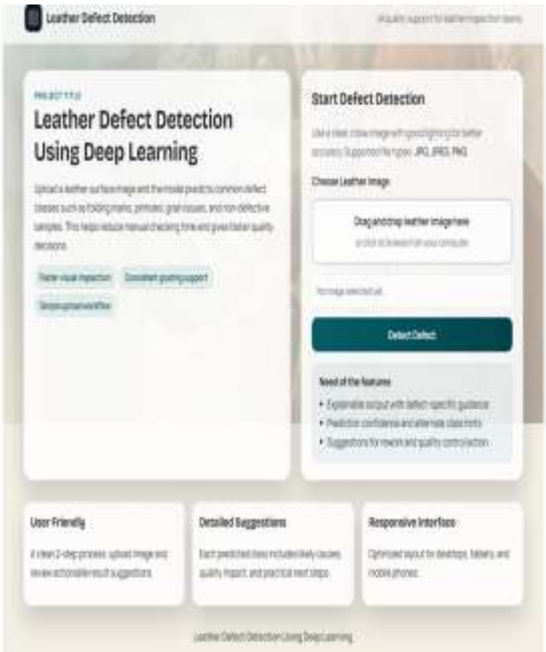
IV. SYSTEM DESIGN

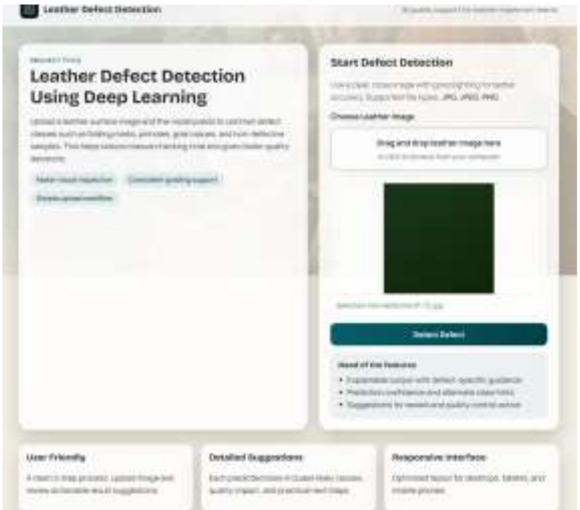
The system design of the Leather Vision project is structured into three main layers: frontend, backend, and database. The frontend provides a user-friendly interface that allows users to upload leather images and view defect detection results. The backend processes the input images using deep learning algorithms, including convolutional neural networks and transfer learning models. Image preprocessing techniques such as normalization, resizing, and augmentation are applied to enhance data quality before feeding it into the model. The backend also manages model training, evaluation, and prediction processes. The database layer stores image datasets, extracted features, and prediction results, ensuring efficient data management and retrieval.





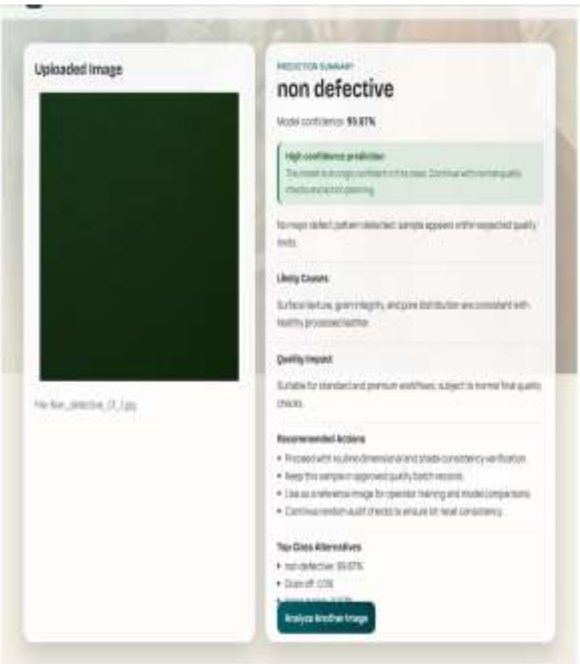
The system follows a modular architecture that includes components such as image acquisition, preprocessing, feature extraction, classification, and result visualization. Data flow diagrams and UML diagrams illustrate the interaction between different modules, ensuring a clear understanding of system functionality. The use of the MVT (Model-View-Template) architecture in Django enhances scalability and maintainability. The system supports real-time processing, enabling quick detection of defects during production. Additionally, the design ensures flexibility and adaptability to different leather types and defect categories. By integrating advanced AI techniques with efficient system architecture, the proposed design provides a reliable and scalable solution for automated leather inspection.

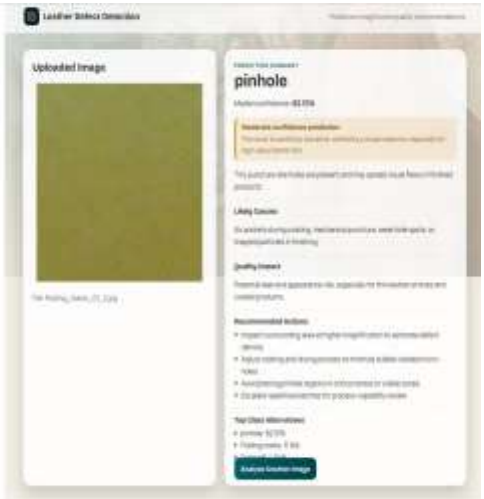




V. RESULTS & ANALYSIS

We have trained a model; 20% of images were selected as a test set randomly and in a stratified manner. We applied class weighing in loss function 1 for the 'Good' class and 3 for 'Anomaly' because in most cases there are 3 times more good images than anomalous ones. The model was trained for at most 100 epochs with early stopping if the train set accuracy reaches 98%. Below are the evaluation results. The train set size is 74 to 297 images. Balanced Accuracy is between 92.1% and 96.0%. In table 1 we show our results and evaluations and in figure 2 confusion matrix. Table 1. Results and evaluations Dataset Name N Images (Train/Test) Test Set Accuracy Test Set Balance Accuracy Test Set Confusion Matrix Leather 297/74 96.0% 93.5% TP = 56, FN = 0, FP=3, TN = 15 . Visualization In most cases, the model produces correct class prediction and precise bounding box if the class is an ‘Anomaly’. However, there are some errors: they are either incorrect class prediction or wrong bounding box location when the class is correctly predicted as an ‘Anomaly





VI. CONCLUSION

The Leather Vision system demonstrates the effectiveness of artificial intelligence in automating leather surface defect detection. By leveraging deep learning techniques such as convolutional neural networks and transfer learning, the system achieves high accuracy and consistency in identifying defects. Traditional manual inspection methods are replaced with an automated approach that reduces human error, improves efficiency, and ensures reliable quality assessment. The integration of image preprocessing techniques enhances feature extraction, while the use of MobileNetV2 improves model performance and reduces training time. The system's ability to perform real-time detection makes it suitable for industrial applications, where speed and accuracy are essential. Furthermore, the modular system design ensures scalability and adaptability to different use cases. By minimizing material wastage and reducing labor costs, the proposed system contributes to improved productivity and economic efficiency in the leather industry. The project highlights the potential of artificial intelligence in transforming traditional inspection processes into intelligent and automated solutions. Future enhancements may include the integration of advanced deep learning models, larger datasets, and improved real-time capabilities to further enhance performance and reliability.

References

1. Liong, S. T., et al. (2020). Deep learning for leather defect detection.
2. Khanal, S. R., et al. (2021). Automated leather inspection systems.
3. Liong, S. T., et al. (2021). Machine vision for defect detection.
4. Chen, Z., et al. (2020). Edge detection techniques for leather defects.
5. Xuekun, W., et al. (2021). Lighting-based defect analysis.
6. Hoang, K., et al. (2020). Machine vision grading system.
7. Gan, Y. S., et al. (2021). Automated classification of leather defects.
8. Khan, T. M., et al. (2022). Dataset development for leather inspection.

9. Jawahar, M., et al. (2021). Texture-based defect detection.
10. Simonyan, K., & Zisserman, A. (2015). VGG networks.
11. Howard, A., et al. (2017). MobileNet architecture.
12. Krizhevsky, A., et al. (2012). CNN for image classification.
13. He, K., et al. (2016). Deep residual learning.
14. Ren, S., et al. (2015). Faster R-CNN.
15. Szegedy, C., et al. (2016). Inception networks.
16. LeCun, Y., et al. (2015). Deep learning overview.
17. Goodfellow, I., et al. (2016). Deep learning fundamentals.
18. Deng, J., et al. (2009). ImageNet dataset.
19. Bishop, C. (2006). Pattern recognition.
20. Cortes, C., & Vapnik, V. (1995). Support vector machines.
21. Rumelhart, D., et al. (1986). Neural networks learning.
22. Zhang, Y., et al. (2019). Industrial defect detection.
23. Redmon, J., et al. (2016). YOLO detection system.
24. Lin, T. Y., et al. (2014). COCO dataset.
25. Chollet, F. (2017). Deep learning with Python.
26. Russakovsky, O., et al. (2015). ImageNet challenge.
27. Girshick, R. (2015). Fast R-CNN.
28. Tan, M., & Le, Q. (2019). EfficientNet.
29. Huang, G., et al. (2017). DenseNet.
30. Shorten, C., & Khoshgoftaar, T. (2019). Data augmentation.