Leather Defect Detection

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***Abstract*—Modern leather industries emphasize producing high-quality leather goods to maintain market competitiveness. However, defects frequently arise during different stages of manufacturing, such as material handling, tanning, and dyeing. Manual inspection of leather surfaces often lacks objectivity and consistency, prompting the adoption of machine vision systems for automated defect inspection. To accurately identify defects like folding marks, growth marks, grain off, loose grains, and pinholes, which have ambiguous textures and fine details, effective image processing algorithms are needed. This research introduces a deep learning-based approach to automate the localization and classification of leather defects using machine vision. Popular convolutional neural networks (CNNs) are trained with images depicting various leather defects, and class activation mapping is used to highlight the relevant defect areas. Networks such as GoogLeNet, SqueezeNet, and ResNet demonstrate superior classification accuracy compared to other advanced neural network architectures.**

***Index Terms*—Convolutional Neural Networks (CNNs), Big Data, Data Preprocessing, Data Quality, Data Validation, Data Ethics**

I. Introduction

The largest export sector of Bangladesh is the textile industry but the one after that is a wild guess. The leather industry has a revenue of an average of one billion US dollars in our country and is the next most promising sector. Back in 2022, the export of leather goods was 1284.74 million USD. This is achieved through duty-free facilities to import sufficient raw materials, necessary infrastructure for leather processing, cheap labor, and machinery for shoe manufacturing. With the slow withdrawal of China, Vietnam, and Brazil, the top producers of leather goods from the sector, it inherently makes it more promising.

For us to grow more, we need to be able to produce more high-quality leather products with high-quality leather. To ensure these each piece of leather goes through quality control but this is still being carried out by manual methods. Defects such as folding marks, grain off, growth marks loose grains, and pinholes are manually detected. However, due to the influence of illumination conditions, workers' different experiences, and the changes in mood, physical strength, and working time, it is easy to cause problems such as low efficiency of inspection and cutting layout. Thus we must automate this process to achieve enhanced efficiency, cut off labor costs,s and even save them from unhealthy dirty working environments. Despite having such a variety of opportunities, we witnessed a decline in revenue in 2023 at around 1107.35 million dollars, 16.02 % less than in 2022. There are a variety of defects but we focussed on addressing the pinhole issues. Pinholes are almost invisible to the naked eye and are detected by feeling the material. This is both time-consuming and tricky. To address this, we've conducted a study on overcoming this by using multiple CNN models to train and test whether they can effectively detect the pinholes and thus automate the process. Achieving pinhole detection would automatically unlock all of the other defects. We have currently used 4 models for our project, mobilenetv2,inceptionnetv3, vgg16, and resnet50 and carefully analyzed and compared each.

II. Related Work

The accurate detection and classification of leather surface defects are crucial for industries reliant on leather, such as footwear and handbag manufacturing. This paper reviews different methods for identifying leather defects, focusing on automated visual inspection using image analysis. These techniques fall into heuristic or machine learning-based methods. The paper discusses deep learning architectures tailored for defect detection and classification and explores traditional methods like texture, wavelet, and classifier-based approaches. Early systems like LeaVis used machine vision for defect detection. Later, methods like Gabor filters, histograms, and edge detection improved defect recognition. The review highlights that many approaches use small datasets, limiting generalizability. Among the classifier-based methods, techniques like SVMs, KNNs, and ANNs exhibit high accuracy by leveraging extensive feature sets. However, the lack of standardized benchmarks and publicly available code remains a challenge for comparative evaluation. In future research, aspects such as data augmentation and simultaneous defect inspection are emphasized for advancing leather defect classification [1]

This paper introduces a method for automatically detecting and classifying leather surface defects using a combination of

Feed-Forward Neural Networks (FNN) and decision trees. The approach aims to reduce misjudgments and costs associated with manual inspections. By integrating FNNs with decision trees, the method leverages the strengths of both techniques, enhancing classification accuracy and reducing computational drawbacks like ”black box” issues, high pruning costs, and long processing times. The defects are extracted from preprocessed images, and features are categorized based on shape, texture, and color. The decision tree classification is guided by supervised learning algorithms, which allow for extracting classification rules through inductive methods. The FNN aids in selecting optimal attributes for improved classification, reducing prediction errors and avoiding redundant pruning. Experiments validate the method’s effectiveness in accurately identifying defects while overcoming issues of traditional decision tree classification. The approach, supported by grants from various institutions, can also be applied to quality control in other industries like textiles, paper, and steel [2].

This paper presents an automated vision-based system for detecting and classifying defects on leather fabric surfaces. The system uses an image-capturing mechanism consisting of a camera and light source to convert the leather surface into images. These images are processed to detect defects like scars, scratches, and pinholes. The defect detection process involves image preprocessing, which includes converting images to a specific color space, reducing brightness, and applying thresholding and segmentation methods to highlight defects. To classify defects, the system employs a Support Vector Machine (SVM) algorithm. The features extracted for classification include color, shape, and texture attributes like color moments, Zernike moments, and texture patterns. The SVM model is set up using standardized data and optimized with the LibSVM library. Experimental results show that the proposed system accurately identifies the size, shape, and position of defects on leather surfaces, achieving over 98% classification accuracy [3].

The paper introduces an automated vision system for detecting and classifying surface defects on leather fabric.The system employs a two-step segmentation process involving thresholding and morphological processing to locate visual defects like lines, holes, stains, wears, and knots.For classification, the system leverages geometric and statistical features, including normalized compactness and first- and second-order statistical measures. A three-stage decision-tree classifier enhances the classification efficiency by sequentially refining defect categorization. Line defects are further checked using a combination algorithm to identify larger defects. The system demonstrated satisfactory results with an overall classification accuracy of 91.25%.The system uses a high-resolution camera and specialized lighting setup to capture high-quality images, and segmentation performance depends on the type of leather under inspection.Statistical features such as inertia and entropy were found to have high discriminatory power in identifying defects. The research emphasizes the importance of automated defect inspection in improving throughput and accuracy while reducing human error in classification tasks [4].

This paper presents an automated leather defect detection system leveraging artificial intelligence and machine vision. The system uses a conveyor-based platform where leather pieces move under a camera for inspection. Images are processed through a deep learning model that segments defects like cuts, wrinkles, and pokes. The system’s design integrates mechanical components, a camera, and a computer for processing and display. Using the MVTEC leather dataset, the authors trained deep learning models to detect defects through image segmentation, specifically employing encoder-decoder architectures like Unet and Segnet, with MobileNetv2 and ResNet50 as feature extraction models. The models were trained for 50 epochs using Python, evaluating performance based on metrics like Intersection over Union (IoU), execution time, and loss. MobileNet was found to be more efficient than ResNet50, providing higher IoU and faster processing. The paper also highlights the challenges of accurately detecting defects in leather due to its pattern complexity and the need for specialized image acquisition systems. The results show that the system achieved a 94% IoU, proving its effectiveness in accurately detecting leather defects [5].

This paper explores the use of image processing techniques to identify leather defects through wavelet-based feature extraction and classification using Support Vector Machines (SVM). Leather defects identified at different stages of processing affect quality control and productivity. Manual inspections are labor-intensive, prone to errors, and inefficient. The paper proposes a method to automatically detect leather defects using wavelet analysis. Captured leather images are processed in the frequency domain using wavelet transform to extract features that can identify defects. Features like Entropy, Energy, Contrast, and Correlation are derived from the wavelet coefficients, and both Wavelet Statistical Features (WSF) and Wavelet Co-occurrence Features (WCF) are used for classification. The SVM classifier is trained with a dataset of 700 leather images, split into 70% for training and 30% for testing. The results indicate that combining both WSF and WCF in the SVM classifier yields high accuracy in identifying defective and non-defective leather samples. The approach shows that image processing techniques using wavelet feature extraction and SVM can effectively automate leather defect detection [6].

The paper introduces a system for automating the leather quality assessment process, which is traditionally done manually and is prone to errors due to fatigue. The system includes steps for capturing leather images and grading their quality based on density and defects. The proposed algorithm assesses leather quality by analyzing the density and defects in images captured by a digital camera. Density is calculated using Fourier spectrum analysis, while defects are identified through histogram analysis. The research identifies four types of defects: holes, pinholes, scratches, and wrinkles. The algorithm utilizes preprocessing techniques like histogram equalization and Gaussian blurring to enhance defect detection, particularly for distinguishing texture patterns. Experiments were conducted using 15 leather samples from Syria. The results demonstrated high accuracy in detecting holes (97.3%) and scratches (94.6%), while detection rates for wrinkles and pinholes were slightly lower. The challenges in detecting pinholes were attributed to variations in lighting conditions and leather properties. The findings suggest that the proposed algorithm effectively automates defect detection and leather grading, despite the limitations in Fourier transform processing for larger image sizes [7].

III. Methodology

A. CNN

A Convolutional Neural Network (CNN) is a type of deep learning algorithm primarily used for processing grid-like data structures, such as images. CNNs are well-suited for image-related tasks because they can automatically detect important features and patterns within images, like edges, textures, shapes, and more complex structures.

1) ***InceptionV3****:* Data Collection: Gather a dataset with images of different leather quality categories. Each image should be labeled according to the quality classification. Data Augmentation: Use augmentation techniques like flipping, rotating, and scaling to increase the dataset's diversity and robustness. Data Preprocessing: Resize images to the input size expected by InceptionV3 (299x299 pixels) and normalize the pixel values. Choose InceptionV3: This model is suitable due to its architecture with multiple filter sizes and its ability to learn complex features. Pretrained Weights: Utilize pre-trained weights (like those from ImageNet) to leverage learned features and speed up training. Replace the Classifier: Replace the final classification layer with one that has the same number of output nodes as the leather quality classes. Freeze Layers: Initially freeze the convolutional layers to maintain the learned features from the pre-trained weights. Compile the Model: Choose an optimizer (like Adam or SGD) and a suitable loss function (like categorical cross-entropy). Train the Model: Train with a low learning rate initially to refine the new classification layer while keeping other layers frozen. Unfreeze Layers: Gradually unfreeze some layers to fine-tune the model on the new dataset while maintaining the existing features. Validation Set: Use a separate validation set to evaluate the model's performance and adjust hyperparameters accordingly. Metrics: Evaluate accuracy, precision, recall, and F1-score to understand the model's strengths and weaknesses. Export the Model: Save the trained model in a format suitable for the intended deployment platform. Optimization: Apply techniques like quantization to optimize the model for mobile or embedded deployment. Monitoring: Track the model's real-world performance to ensure it maintains high accuracy. Retraining: Regularly update the model with new data to ensure it adapts to changing conditions and maintains accuracy. The InceptionV3 model, with its advanced architecture and multi-scale feature learning capabilities, can be effective for leather quality classification with proper training and fine-tuning. Range: With high-quality data and proper fine-tuning, InceptionV3 can achieve accuracies ranging from 85% to 95% for leather quality classification. Variation: The actual accuracy may vary based on the quality of the dataset, the model's training approach, and evaluation criteria.

2) ***resnet 50****:* Data Collection: Collect images representing different qualities of leather. Ensure the dataset has labeled images with varying quality grades. Data Augmentation: Apply transformations like flipping, rotation, scaling, and lighting adjustments to augment the dataset. Data Preprocessing: Resize the images to the input size expected by ResNet50 (224x224 pixels) and normalize pixel values. Choose ResNet50: This model uses residual connections to learn complex features and helps avoid vanishing gradient problems. Pretrained Weights: Leverage a pre-trained ResNet50 model (trained on ImageNet) to benefit from learned features. Replace the Classifier: Replace the final fully connected layer with a new layer that has the same number of output classes as the leather quality categories. Freeze Layers: Initially freeze the convolutional layers to retain their learned features from pretraining. Compile the Model: Use an optimizer like Adam or SGD and a loss function such as categorical cross-entropy. Train the Model: Train with a low learning rate to refine the classifier, using a validation set to tune hyperparameters. Unfreeze Layers: Gradually unfreeze some layers to fine-tune the convolutional features for the new dataset. Validation Set: Assess the model's performance on a separate validation set to understand its strengths and weaknesses. Metrics: Measure accuracy, precision, recall, and F1-score to evaluate the model's performance. Export the Model: Save the model in a format suitable for your deployment platform. Optimization: Use techniques like quantization to reduce the model's size and improve its inference speed if needed. Monitoring: Monitor the model's real-world performance to ensure it maintains accuracy. Retraining: Regularly retrain the model with new data to adapt to changing conditions. Using ResNet50 for leather quality classification can be effective due to its deep architecture and residual connections, which improve feature learning and model accuracy Range: With a well-curated dataset and proper training, ResNet50 can achieve accuracies between 85% and 95% for binary or multiclass leather quality classification tasks. Variation: The accuracy can vary based on factors like dataset quality, model tuning, and training strategy.

3) ***MobileNetV2****:* Data Collection: Obtain a dataset containing images representing different grades or qualities of leather. Each image should be labeled according to its quality.Data Augmentation: Since leather patterns can vary widely, apply data augmentation techniques such as rotation, flipping, and scaling to increase the dataset size and diversity. Data Preprocessing: Preprocess the images to match the input size expected by MobileNetV2, which is 224x224 pixels. Normalize pixel values to have a range between 0 and 1. Choose MobileNetV2: This model is efficient and suitable for mobile and embedded devices due to its small size and fast inference. Pretrained Weights: Use MobileNetV2 with weights pre-trained on a large dataset like ImageNet for faster convergence. Replace the Classifier: Replace the final layer of MobileNetV2 with a new fully connected layer that has the same number of outputs as the leather quality classes. Freeze Layers: Initially, freeze the weights of the convolutional layers to retain the learned features and avoid overfitting on the small leather dataset.Compile the Model: Choose an optimizer like Adam and a suitable loss function such as categorical cross-entropy. Train the Model: Train the model with a relatively small learning rate, monitoring the validation loss to avoid overfitting. Unfreeze Layers: Gradually unfreeze some layers to fine-tune the model further. Evaluate on Validation Set: Use a validation dataset to assess the model's performance and fine-tune hyperparameters if necessary. Metrics: Focus on accuracy, precision, recall, and F1-score for evaluating the model. Convert to TFLite: Convert the trained model to TensorFlow Lite (TFLite) format for deployment on mobile devices. Optimization: Apply quantization and other optimization techniques to reduce the model's size and improve inference speed. Monitoring: Monitor the deployed model's performance and accuracy, gathering feedback for further improvements. Maintenance: Periodically retrain the model with new data to maintain its accuracy over time. By following these steps, you can effectively implement and deploy a MobileNetV2-based model to classify leather quality. Range: For high-quality datasets and proper training, MobileNetV2 can achieve accuracies ranging from 80% to 95% for binary or multiclass leather quality classification. Real-World Performance: Performance may vary based on the actual deployment environment, lighting conditions, and other factors.

*4) **VGG16 Model**:* Data Collection: Gather a dataset containing images of leather categorized by their quality levels. Data Augmentation: Apply data augmentation techniques like flipping, rotation, scaling, and contrast adjustments to expand and diversify your dataset.Data Preprocessing: Resize images to the input size expected by VGG16, which is 224x224 pixels. Normalize the pixel values to a range of 0 to 1 or -1 to 1. Choose VGG16: This model, with its deeper architecture and multiple convolutional layers, can capture detailed features useful for classifying leather quality. Pre-trained Weights: Use a version of VGG16 pre-trained on a large dataset like ImageNet to leverage pre-learned features. Replace the Classifier: Replace the top layer (fully connected layers) of the model with a new fully connected layer suited to the number of leather quality classes. Freeze Layers: Freeze the convolutional layers initially to retain their pre-trained features and focus on training the new classification layer. Compile the Model: Choose an optimizer like Adam or SGD, and use an appropriate loss function such as categorical cross-entropy. Train the Model: Train the model using a low learning rate initially to refine the new classification layer. Unfreeze Layers: Gradually unfreeze more layers of the model to fine-tune the convolutional features while maintaining the learned features from the pre-trained weights. Validation Set: Use a validation dataset to assess the model's performance and fine-tune the hyperparameters. Metrics: Evaluate accuracy, precision, recall, and F1-score to understand the model's classification performance. Export the Model: Save the trained model in a format suitable for your deployment platform. Optimization: Optimize the model if necessary for deployment using techniques like quantization or pruning. Monitoring: Track the model's performance post-deployment to ensure it meets accuracy requirements in real-world settings. Retraining: Regularly update the model with new data to adapt to changing conditions and maintain accuracy. Using the VGG16 model for leather quality classification can be effective due to its deep architecture, but it requires careful training and fine-tuning to ensure high accuracy. Range: With a high-quality dataset and careful tuning, the VGG16 model can achieve accuracies ranging from 85% to 95% for binary or multiclass leather quality classification. Variation: Accuracy may vary based on factors like dataset diversity, model fine-tuning, and training strategy.

IV. Experimental Analysis

A. Dataset

The Leather Defect Detection and Classification dataset leverages deep learning-based convolutional neural networks (CNNs) for automated leather defect identification, achieving high accuracy in classifying and localizing defects like folding marks and growth marks. The dataset contains a total of 3,600 files, each representing one of the following defect types: folding marks, grain off, growth marks, loose grains, non-defective, and pinholes. Each defect type has 600 files. Our work specifically focuses on non-defective samples and those with pinholes. By comparing the files for both defect types, the system effectively distinguishes between pinholes and non-defective products, enhancing defect detection and quality assurance.

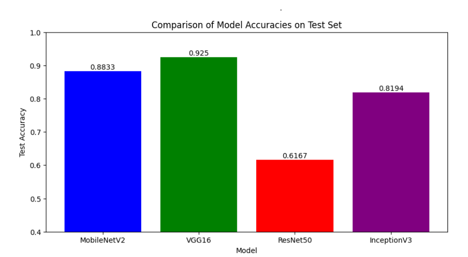

Fig. 1. Bar Chart Comparison

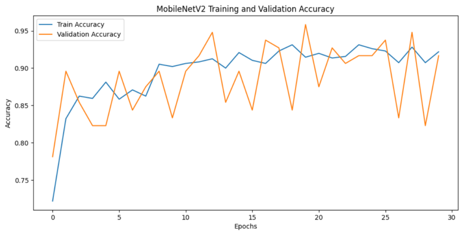

Fig. 2. Epoch vs Accuracy

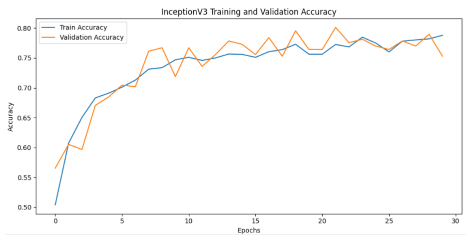

Fig. 3. inception

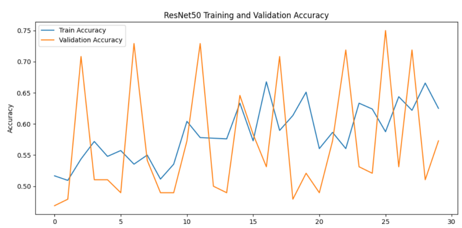

Fig. 4. Resnet

B. Pre-Processing

The provided code outlines a comprehensive process for data preprocessing to prepare a dataset for a deep learning model. The main steps include downloading the dataset from Kaggle, organizing it into training, validation, and testing sets, and visualizing the data to ensure everything is set up correctly.

- Installing Dependencies: Install the required Python libraries and authenticate with Kaggle.
- Download and Extraction: Download the dataset using the Kaggle API and extract it to a specified directory.
- the Dataset: Create directories for the training, testing, and validation sets and move images to these folders according to their class.
- Splitting: Split the dataset into training, validation, and testing subsets.
- Visualization: Plot sample images from each class in the training set to visually confirm the data is organized correctly.

C. Results

In this section, we present a comprehensive comparison of the performance of four different classification models on both imbalanced and balanced datasets. Table I illustrates the results..

CNN: In the context of imbalanced datasets our study reveals that After evaluating different deep learning models for the task, it was found that VGG16 provided the best performance, likely due to its simpler architecture, which may suit this particular problem well. VGG16 is known for its sequential architecture, making it relatively easier to train and apply. Its performance can often be attributed to its deep feature extraction capabilities that effectively capture the essential patterns in the data.

On the other hand, ResNet50, despite its reputation for handling deeper networks due to its residual connections, did not perform as well in this specific scenario. The more complex architecture of ResNet50 might be overfitting to the dataset or not effectively learning the relevant features needed for this particular task.

TABLE I
MOBILENETV2, VGG16, RESNET50, INCEPTIONV3

Model	**MobileNetV2 (%)**	**VGG16 (%)**	**ResNet50 (%)**	**InceptionV3 (%)**
Accuracy	88.33%	92.50%	61.67%	81.94%

V. Conclusion and Future Work

The Leather Defect Detection and Classification dataset demonstrates the potential of deep learning-based convolutional neural networks in accurately identifying and classifying leather defects. Focusing on non-defective samples and those with pinholes, the system effectively distinguishes between defect types, significantly improving the precision of automated quality control in the leather industry. This approach ensures a more consistent and objective inspection process compared to manual methods, enhancing production efficiency and maintaining market competitiveness.

Future work could involve expanding the dataset to include additional types of leather defects, allowing for a more comprehensive classification system. Improving the model's accuracy in detecting subtle defects like growth marks and grain off could also be beneficial. Additionally, integrating advanced techniques like transfer learning or data augmentation could improve the system's adaptability to new defect types and production environments. Finally, real-time implementation of these models in production lines could further streamline the inspection process, reducing inspection times and associated costs.

VI. Contributions

1) Concept development - Souharda Bhattacharjee
2) Method & Code - Md. Ismam Hossain Redwan
3) Validation - Asim Ajwad
4) Data procurement - Joyanta Chakraborty

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