ISSN No:-2456-2165

Enhancing Warehouse Operations Through Artificial Intelligence: Pallet Damage Classification with Deep Learning Insights

Mohan Doss Nadarajan[1]
[1]Research Associate, Innodatatics, Hyderabad, India

Sai Raghava[2]
[2]Research Associate, Innodatatics, Hyderabad, India

Sandeep Giri[3]
[3]Mentor, Research and Development, Innodatatics, Hyderabad, India

Ranjitha.P[4]
[4]Team Leader, Research and Development, Innodatatics, Hyderabad, India

Bharani Kumar Depuru[5*]
[5]Director, Innodatatics, Hyderabad, India

Corresponding Author:- Bharani Kumar Depuru[5*] OCR ID: 0009-0003-4338-8914

Abstract:- Wooden pallets are widely used in the supply chain, yet they are susceptible to damage during storage and transportation. This susceptibility shortens the pallets' service life and results in significant costs due to product loss and pallet replacement. Automated pallet inspection can play a crucial role in identifying and preventing damaged pallets from entering the supply chain.

Machine learning models, such as CNNs, SVMs, VGG16, VGG19, MobileNet, DenseNet, and ResNet51, have emerged as promising new approaches for automated pallet inspection. These models can be trained to automatically identify and classify pallet damage from images. This is achieved by training the model on a large dataset of labeled images of pallets with different types of damage, such as good, repair, and dismantle.

Once trained, a machine learning model can swiftly and accurately classify new pallets. To do this, one simply feeds the model an image of a pallet and receives a prediction of the pallet's damage status. The predicted results are then stored in a database for future reference and analysis.

The objective of this research is to develop an automated pallet inspection architecture with three key categories: 'good,' 'repair,' and 'dismantle.' The architecture will be based on a machine learning model, such as a CNN, SVM, or ResNet, trained on a substantial dataset of labeled images of pallets with various types of damage.

Once trained, the model will be deployed in a real-time system for inspecting new pallets. The system will rapidly and accurately classify pallets and provide recommendations for categorizing them as 'good,' 'repair,' or 'dismantle.' The automated pallet inspection architecture holds the potential to enhance the efficiency and accuracy of pallet inspection, reduce reliance on manual inspection, and effectively identify and prevent damaged pallets from entering the supply chain. This, in turn, can lead to substantial cost savings and reductions in product loss.

Keywords:- *Automated Pallet Inspection, Artificial Intelligence, CNNs, SVMs, ResNets, Pallet Classification, Pallet Damage Classification, ResNet for Pallet Inspection, Pallet Dismantle Prediction, Real-Time Pallet Inspection, Wooden Pallet Quality Control.*

I. INTRODUCTION

This article proposes a new automated pallet inspection architecture based on the CRISP-ML(Q) methodology available in the 360DigiTMG website (ak.1) [Fig.1]. The architecture is designed to classify pallets into three categories: **Good**, **Repair**, and **Dismantle**.

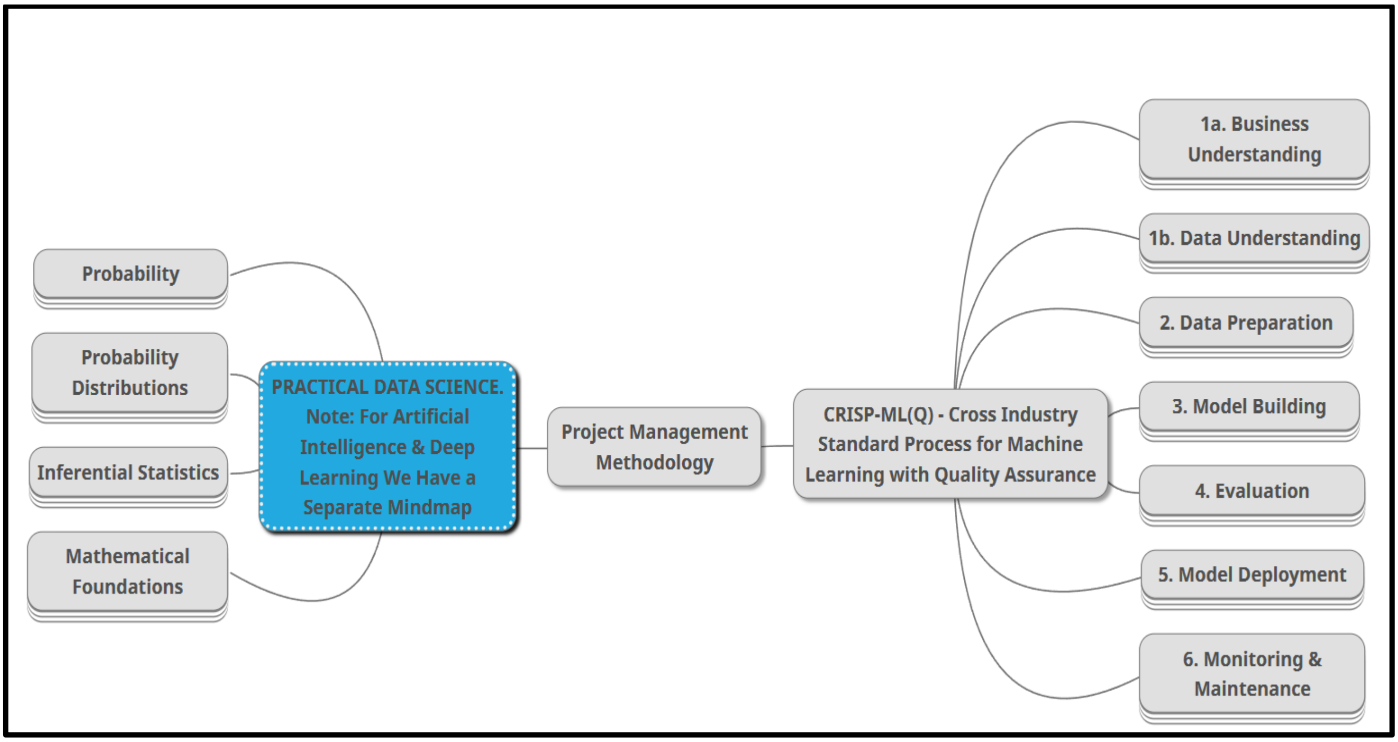

Fig 1 The above Figure Displays the CRISP-ML(Q) Architecture that we used for this Research Project.
(Source: Mind Map - 360DigiTMG)

In the Business Understanding phase, we identified the following business problem: wooden pallets are widely used in the supply chain, but they are susceptible to damage during storage and transportation [3]. This damage can lead to product loss and pallet replacement, which can be costly [7]. Automated pallet inspection using ML can help to identify and prevent damaged pallets from entering the supply chain [1].

In the Data Understanding phase, we explored and understood the data that we would be using to train the ML model. The data consists of images of wooden pallets with different types of damage. We also identified some data cleaning and preprocessing that needed to be done, such as removing noise from the images, resizing, and Normalizing [10, 11].

In the Data Preparation phase, we cleaned, preprocessed, and transformed the data into a format of JPG, PNG, and JPEG, that was suitable for model training. We also split the data into training and test sets [1].

In the Modeling phase of the CRISP-ML(Q) methodology, we will alter and add the machine learning models mentioned above to improve the performance of our pallet damage classification model. We will do this by:

- Choosing the right model for our specific task.
- Altering the model architecture to improve its performance on our specific task.
- Adding new data to the training set to improve the model's performance
- Training the model [13].

Once the model is trained, we will evaluate its performance on a held-out test set to ensure that it meets our requirements. If the model does not meet our requirements, we will go back to the Modeling phase and alter the model further [11, 6].

Once we are satisfied with the model's performance, we will deploy it to production so that it can be used to inspect pallets in real time. The model will be integrated into a software application allowing users to upload pallet images and receive predictions of the pallet's damage status [11, 6].

The proposed automated pallet inspection architecture, based on the CRISP-ML(Q) methodology and with a focus on altering and adding machine learning models, has the potential to improve the efficiency and accuracy of pallet inspection, reduce the reliance on manual inspection, and identify and prevent damaged pallets from entering the supply chain. This can lead to significant cost savings and reductions in product loss [1, 7].

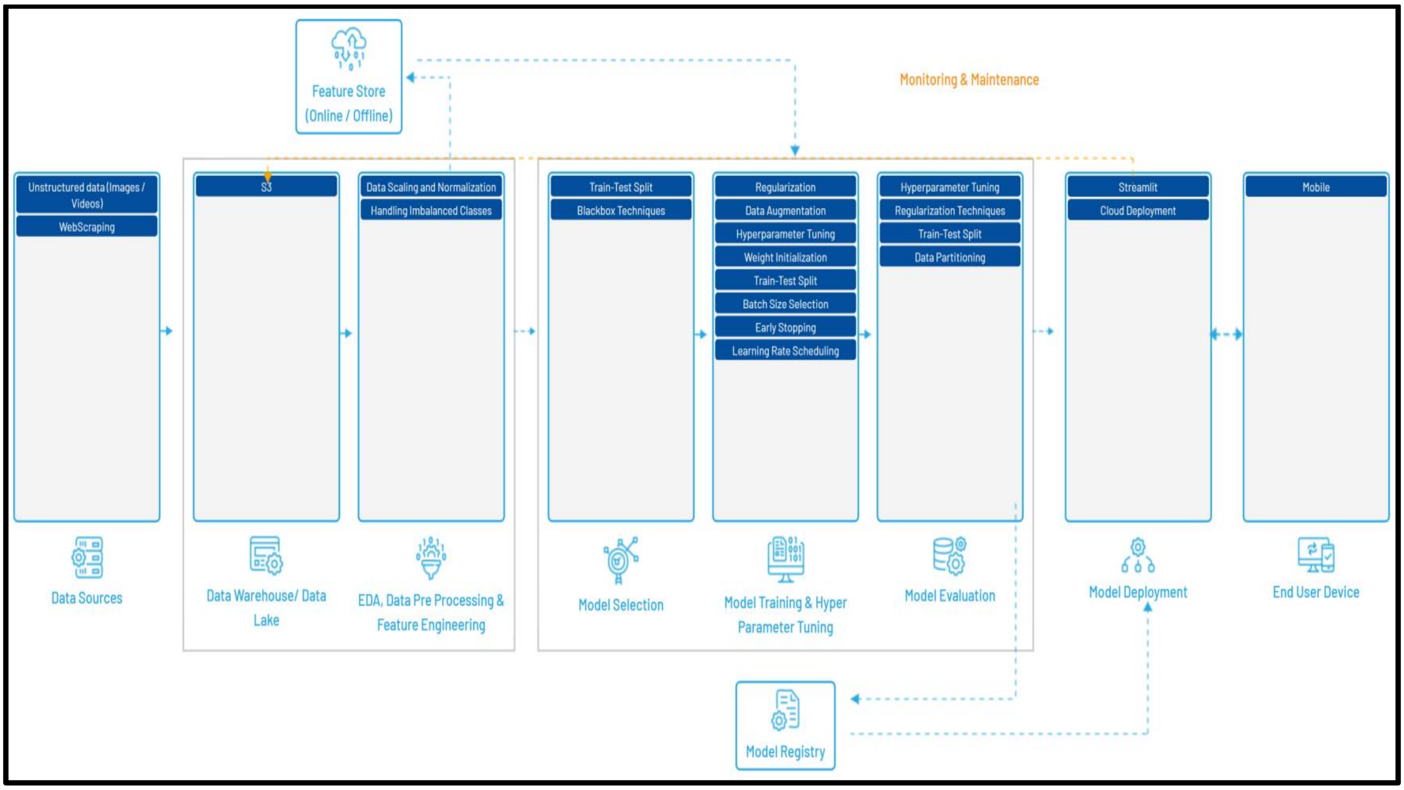

Fig 2 ML Workflow Architecture used for the Research - A Detailed overview of the Deep Learning Pipeline for Accurate Pallet Damage Classification
(Source: ML Workflow - 360DigiTMG)

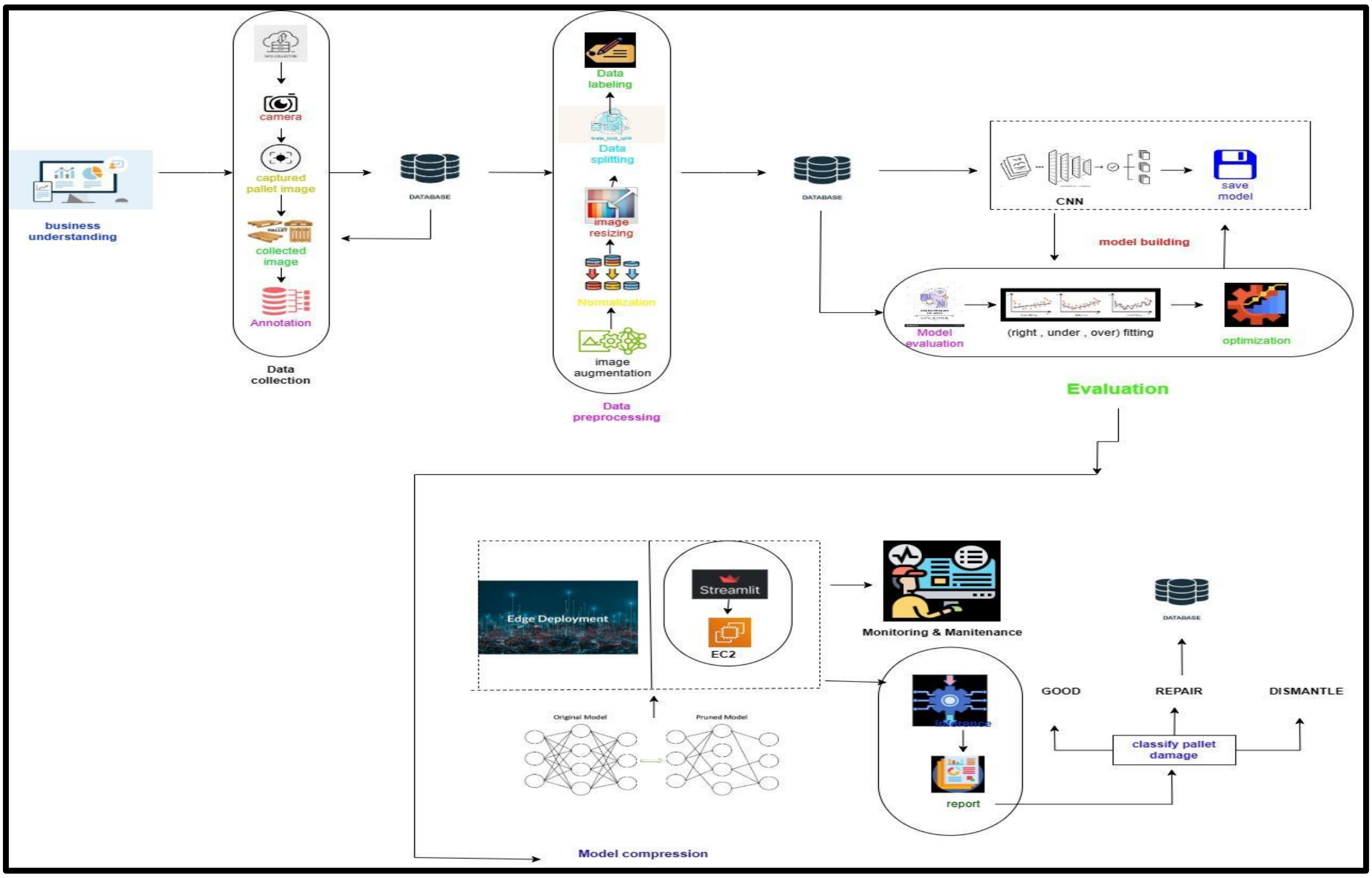

Fig 3 Architecture Diagram: Showcasing the Components and Flow of Data for Automated Pallet Damage Detection and Classification using Computer Vision and Machine Learning Techniques.
(Source: ML Workflow | 360DigiTMG)

A. Data Collection

In this section, we describe the methodology employed for the acquisition of damaged pallet images [Fig.2, 3], which form the foundation of our research dataset, we have used the interactive ML workflow diagram hosted as open-source by 360DigiTMG (ak.2) [Fig.2]. The collected dataset encompasses three distinct categories: "Good Pallets", "Repair Pallets" and "Dismantle Pallets" [Table.2] each vital for the objectives of our study.

➢ *Data Source*

We obtained damaged pallet images from two primary sources:

Table 1 Data Description

Data Description	Values
Images from Client Site	314
Images from Internet	638
Total Raw Images	952
No. of Images after augmentation	11,517
Dimensions of Image	224*224
Image Format	JPEG
No.of Training Images	11,517
No.of Testing Images	285
Total size of the Data	5.2GB

- *Internet Sources:*

A subset of images was sourced from various online platforms, such as image databases and websites. These images were collected using a web scraping approach [Fig.2, 3] with a focus on images tagged or categorized as damaged pallets. In total, 638 images [Table.1] were gathered from online sources.

- *Client Warehouse:*

The remaining portion of our dataset was procured through a collaborative effort with a client's warehouse facility. The warehouse, specializing in the storage and handling of pallets, provided access to on-site damaged pallets for photographic documentation. This contributed 314 images [Table.1] to our dataset.

- *Total Raw Images Collected:*

Our combined data collection efforts resulted in a total of 952 raw images [Table.1], forming the basis for our subsequent analysis and research.

Table 2 The Criteria for Classifying Pallets based on the Number of Damaged Components are Described in the table above

S.No	Pallet type	Pallet Components	Damage
1	Good	27	None
2	Repair	27	<= 8 components or fewer missing or broken boards, cracks, rots, splinters
3	Dismantle	27	More than 9 components are damage,Termite effected

➢ *Types of Damage: the Dataset Represents a Wide Range of Pallet Damage [7], Including*

- Cracks [Table.2]: Cracks in the wood can be caused by impact, overloading, or over-drying.
- Splinters [Table.2]: Splinters can be caused by rough handling or by nails or screws that have not been properly countersunk.
- Missing or broken boards [Table.2]: Boards can be missing or broken due to impact, overloading, or simply wear and tear [7].
- Rot [Table.2]: Rot can be caused by moisture and can weaken the wood, making it more susceptible to other types of damage.
- Insect damage: Insects, such as termites and carpenter ants, can damage the wood, making it weaker and more susceptible to other types of damage.

B. Data Preprocessing

➢ *Image Resizing:*

Resizing images [Fig.3] is a critical pre-processing step in computer vision. Principally, deep learning models train faster on small images. A larger input image requires the neural network to learn from four times as many pixels, and this increases the training time for the architecture [10].

➢ *Image Normalization:*

Normalization [Fig.3] in PyTorch involves the transformation of image pixel values into a standardized format, which is particularly important for machine learning tasks involving image data. One common step in this process is converting images into PyTorch tensors, wherein pixel values are rescaled to fit within the 0.0 to 1.0 range. This normalization is achieved by dividing each pixel value by 255.0, a standard practice in image data preprocessing. Normalizing pixel values to this range ensures consistency and facilitates effective model training and generalization, making it a fundamental step when working with image data in PyTorch and similar deep learning frameworks.

➢ *Data Splitting:*

Data splitting [Fig.3] is a crucial step in machine learning, as it enables us to train and evaluate our models effectively. In the context of wooden pallet damage classification, we can split the dataset into three subsets: training and test [1, 4].

Split the dataset into training and test sets. A common split might be 70% for training and 30% for testing [1]. The training set is used to train the model and the test set evaluates the final model's performance [11].

➢ *Data Augmentation:*

Augmentation [Fig.3] is a transformative technique used to expand a dataset by generating new images from existing ones. By applying various adjustments, slight modifications are made to the original images, enhancing their diversity and usefulness. These alterations involve rescaling pixel values to a normalized range (1./255), rotating images by up to 20 degrees (rotation_range=20), introducing horizontal and vertical shifts by 20% of the image dimensions (width_shift_range=0.2, height_shift_range=0.2), applying shear distortions within a range of 20% (shear_range=0.2), zooming images within a 20% range (zoom_range=0.2), and randomly mirroring images horizontally (horizontal_flip=True). These augmentation operations collectively create new instances that expose machine learning models to a wider array of scenarios, resulting in improved model robustness and performance when faced with diverse real-world image variations. Data augmentation helps the model generalize better and reduces overfitting [2, 10].

C. Machine Learning Models:

➢ *CNNs (Convolutional Neural Networks)*

CNNs are a type of deep learning model that is specifically designed for image classification tasks. CNNs work by extracting features from images using a series of convolutional and pooling layers. The extracted features are then used to train a classifier to predict the class of the image [1, 5, 11, 12].

- *CNNs have Several Advantages for Automated Pallet Inspection:*

✓ CNNs can learn to extract features from images that are relevant for pallet classification, such as the presence of cracks, splinters, and missing or broken boards.
✓ CNNs are robust to noise and other variations in the data. This is because CNNs learn to extract features from images in a hierarchical manner, starting with simple features and gradually moving to more complex features.
✓ CNNs can be trained to achieve very high accuracy on pallet classification tasks.

➢ *SVMs (Support Vector Machines)*

SVMs are a type of machine-learning model that can be used for classification and regression tasks. SVMs work by finding a hyperplane that separates the data into two classes. The hyperplane is chosen to maximize the margin between the two classes, which makes the model more robust to noise [13].

- *SVMs have the following Advantages for Automated Pallet Inspection:*

✓ SVMs are robust to noise and other variations in the data.
✓ SVMs can be trained to achieve good accuracy on pallet classification tasks, even with a small amount of training data.

➢ *VGG16 and VGG19*

VGG16 and VGG19 are pre-trained CNN models that have been trained on a large dataset of images. These models can be used for image classification tasks without the need for extensive training.

- *VGG16 and VGG19 have the following Advantages for Automated Pallet Inspection:*

✓ VGG16 and VGG19 have been shown to achieve state-of-the-art results on many image classification benchmarks.
✓ VGG16 and VGG19 can be used for automated pallet inspection without the need for extensive training.

➢ *Mobile Net*

Mobile Net is a lightweight CNN model that has been designed for mobile devices. Mobile Net is able to achieve comparable accuracy to other CNN models but with a much smaller number of parameters and FLOPs (floating-point operations).

- *Mobile Net has the following Advantages for Automated Pallet Inspection:*

✓ Mobile Net is a lightweight CNN model that is efficient enough to run on mobile devices. This makes it a good choice for automated pallet inspection systems that need to be deployed on mobile devices, such as robots and drones.
✓ Mobile Net can achieve good accuracy on pallet classification tasks, even though it is a lightweight model.
✓ Mobile Net and MobileNetV2: Mobile Net and MobileNetV2 are lightweight CNN models that are designed for mobile devices. They are able to achieve good accuracy on image classification tasks, even though they are very efficient [2].

➢ *Shuffle Net*

Shuffle Net is a lightweight CNN model that uses a channel shuffle operation to improve the efficiency of the model. Shuffle Net is able to achieve good accuracy on image classification tasks, even though it is very efficient.

➢ *Squeeze Net*

Squeeze Net is another lightweight CNN model that is designed for efficiency and compactness. It achieves this by using fire modules and squeeze layers. Squeeze Net is able to achieve good accuracy on image classification tasks, even though it is very efficient and compact. This makes it a good choice for pallet damage classification tasks where efficiency, compactness, and accuracy are all important.

➢ *Dense Net*

Dense Net is a CNN model that uses dense connectivity to improve the efficiency of the model. Dense Net is able to achieve state-of-the-art accuracy on image classification tasks, but it is less efficient than other CNN models.

➢ *ResNet51*

ResNet51 is a CNN model that uses residual connections to improve the performance of the model. Residual connections allow the model to learn deeper representations of the data without overfitting.

- *ResNet51 has the following Advantages for Automated Pallet Inspection:*

- ✓ ResNet51 has been shown to achieve state-of-the-art results on many image classification benchmarks.
- ✓ ResNet51 is robust to noise and other variations in the data.
- ✓ ResNet51 can be trained to achieve very high accuracy on pallet classification.

Table 3 Shows the Train Accuracy and Test Accuracy along with Hyperparameters of 10 Different Deep Learning Models.

S. no	Model	Hyferparameters	Train Accuracy	Test Accuracy
1	CNNs	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.76	0.75
2	SVMs	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.95	0.65
3	VGG16	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), kernel_regularizer=l2(0.01), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.99	0.85
4	VGG19	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.98	0.75
5	MobileNet	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.88	0.51
6	ResNet	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.3	0.8	0.5
7	ShuffleNet v2	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), kernel_regularizer=l2(0.01), optimizer=adam, relu and sigmoid activation function, dropout = 0.2	0.69	0.45
8	SqueezeNe t	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	74	0.55
9	DenseNet	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.9	0.78
10	ResNet51	Batch size - 50, epochs - 50, agumentation (rescale=1./255, rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True), optimizer=adam, relu and sigmoid activation function, dropout = 0.5	0.9	0.82

D. Deployment Strategy

Model deployment refers to the process of making a trained model available for use in a production environment.

This involves taking the trained model and integrating it with an application or system so that it can be used to make predictions or generate output.

Streamlit is a Python-based open-source web application framework used for building interactive and data-driven applications. It enables developers to quickly build web applications using Python by providing a simple and intuitive API for building web interfaces.

- ➢ *Streamlit Application*

The Streamlit interface [Fig.4] enables users to upload new images. The uploaded image will undergo analysis by the model, predict the class [Fig.5] the image belongs to, and save the result in the database [Fig.6].

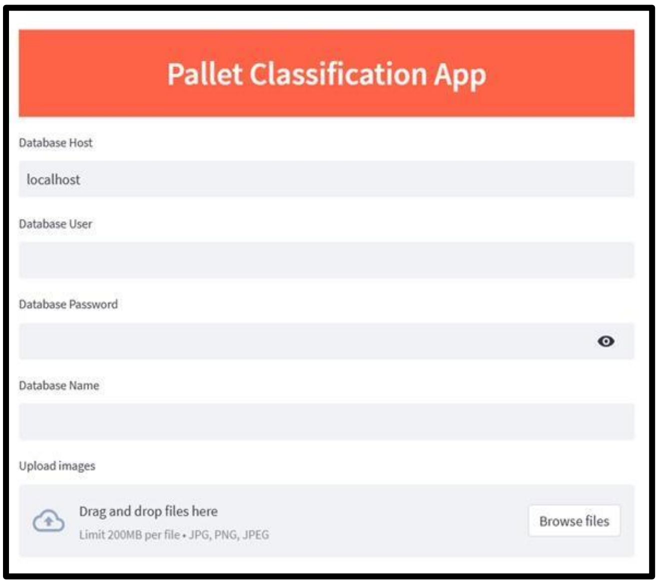

Fig 4 Deployment using Streamlit Application

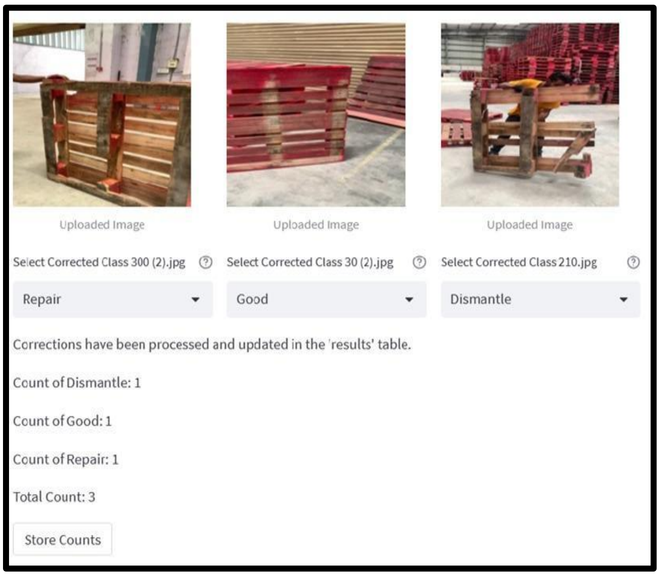

Fig 5 The above Figure Depicts the Predicted Pallet Class and Count

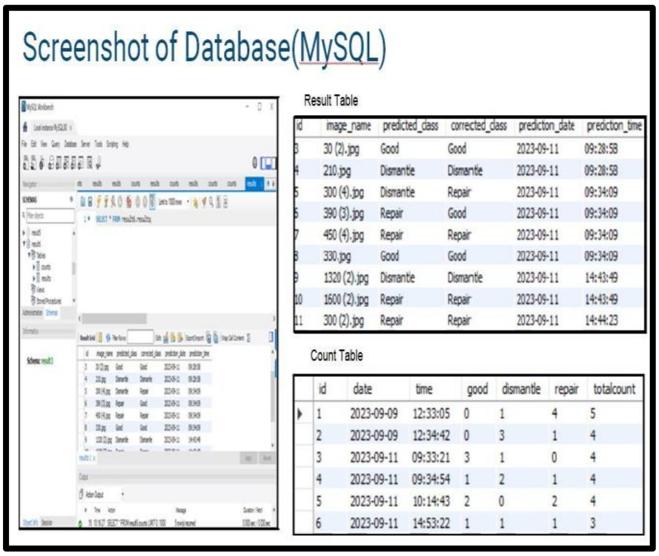

Fig 6 Store the Predicted Result in MySQL

II. RESULTS AND DISCUSSION

During the training process of pallet damage classification, we explored the performance of 10 distinct models using a dataset of 932 wooden pallet images. Among these models, Resnet51 was the best-performing model [Table.3], achieving a training accuracy of 90% and a test accuracy of 82%. This outcome indicates ResNet51 promise for this classification task, though all models showed relatively high test accuracy, indicating their capability to learn the task. The superior performance of ResNet may be attributed to its depth and large parameter count, enabling it to grasp intricate data patterns. Additionally, ResNet excels in learning long-range dependencies, crucial for image classification where pixel relationships can span great distances. Despite a lower training accuracy than some other models, ResNet's ability to generalize well to unseen data is reflected in its highest test accuracy. Further evaluation of a larger dataset and comparisons with other state-of-the-art models are essential steps before deploying ResNet in a production environment.

III. CONCLUSION

Artificial intelligence and computer vision have revolutionized wooden pallet classification by swiftly and accurately analyzing key features. ResNet51 shows promise with 90% train accuracy and 82% test accuracy [Table.3], but further evaluation is necessary. These technologies detect anomalies, ensuring pallet quality and safety. Object detection algorithms, including ResNet, offer efficient real-time classification. Ongoing research focuses on enhancing accuracy and scalability, aligning with the logistics industry's pursuit of efficient and sustainable supply chain management.

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