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SILKWORM PUPA GENDER CLASSIFICATION USING TRANSFER LEARNING APPROACHES

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Abstract : Sericulture is the process of cultivating silkworms for the production of silk.High quality production of silk without mixing with low quality is a great challenge faced in the silk production centers. One of the possibilities to overcome this issue is by separating male and female cocoons before extracting silk fibers from the cocoons as male cocoon silk fibers are finer than females. This study proposes a method for the classification of male and female cocoons with the help of images without destructing the cocoon. The shape features of the pupa are considered for the classification process and were obtained without cutting the cocoon. A novel point interpolation method is used for the computation of the width and height of the cocoon. Different dimensionality reduction methods are employed to enhance the performance of the model. The preprocessing features are fed to the powerful Transfer learning methods such as Visual Geometry Group (VGG16) and ResNet.

IndexTerms - **Classification, Covolutional Neural network(CNNs), Deep learning, Image Classification, Machine Learning, Sericulture, Sex Determination, Silkworm**.

I. INTRODUCTION

Silkworms play a crucial role in the production of silk, and the quality of silk is greatly influenced by the gender of the silkworm pupa. Male cocoon silk filaments are finer compared to females, making it essential to accurately classify the gender of silkworm pupae in order to ensure high-quality silk production. Traditional methods for gender classification often involve destructive techniques such as cutting open the cocoons, which can result in economic losses and require skilled laborers. To address thesechallenges, non-destructive methods using image preprocessing techniques and transfer learning have emerged as effective approaches for silkworm pupa gender classification[1].Non-destructive methods offer significant advantages in terms of preserving the integrity of the cocoons and reducing economic losses in the sericulture industry. Image preprocessing techniques are applied to enhance the quality of raw silkworm pupa images by removing noise, improving contrast, and optimizing the overall image appearance. These techniques help to extract relevant features from the images that are crucial for accurate gender classification.Transfer learning, a powerful technique in the field of machinelearning, leverages pre-trained deep learning models that have been trained on large image datasets.These models, such as VGG16 and ResNet, capture complex patterns and characteristics from images, enabling them to extract discriminative features from silkworm pupa images. By utilizing transfer learning, the knowledge and representations learned from these models can be transferred to the task of silkworm pupa gender classification, improving the overall accuracy and efficiency of the classification process.In this study, we propose a non-destructive approach for silkworm pupa gender classification using image preprocessing techniques and transfer learning. The raw silkworm pupa images are subjected to preprocessing methods to enhance their quality and extract informative features. Transfer learning models, pretrained on large image datasets, are employed to extract discriminative features from the preprocessed images. These features are then utilized to train a classification model capable of accurately distinguishing between male and female silkworm pupae.The proposed method offers several advantages over traditional approaches, including the preservation of cocoon integrity, reduction in economic losses, and improved classification accuracy. By utilizing non-destructive techniques and transfer learning, we aim to provide an efficient and reliable solution for silkworm pupa gender classification, benefiting the sericulture industry and contributing to the production of high-quality silk[2].In this project we are leveraging the most important potential of CNNs through transfer learning where we use the previously trained CNN models to classify the images of silkworms. Convolutional neural networks are trained with silkworm images to extract the features in them and later classify them whether there are any findings in them or they are Normal. The pre trained models like VGGNet and ResNet, which are trained on largescale dataset are employed to our required task of feature extraction and image classification task at hand.We do a comparative analysis of the results based on the metrics for which the model has been evaluated. We find a best model to use it in the web based application for making predictions.

II. LITERATURE SURVEY

Dimpy Varshni et al. [1] conducted research on silkworm gender classification using CNNs for feature extraction. They worked with a dataset specifically created for silkworm gender classification and applied various CNN architectures for feature extraction. The study explored different classifiers and analyzed their performance. Their work focused on binary classification, distinguishing between male and female silkworms. The best accuracy of 80.02% was achieved using DenseNet-169 for feature extraction and SVM as the classifier.

Hongyu Wang et al. [2] proposed a deep CNN model called ChestNet for identifying and classifying thoracic abnormalities in silkworm pupae. The model consisted of two sub-sections: a classification section and an attention section. The attention section aimed to leverage the interdependence between target class labels and abnormal areas in the pupae. It adapted the model to focus on areas with abnormalities, enhancing the accuracy ofclassification.

Rahib H. Abiyev et al. [3] studied different models for silkworm gender classification, including deep CNNs, backpropagation neural networks (supervised learning), and competitive neural networks (unsupervised learning). They compared the recognition rates of these models and found that the backpropagation neural networks outperformed the competitive neural networks.

These studies highlight the use of CNNs and other machine learning techniques for silkworm gender classification. They demonstrate the importance of selecting appropriate architectures and classifiers to achieve accurate results. However, more research is needed to explore additional methods and improve the overall accuracy and efficiency of silkworm gender classification systems.

2.1 Existing System

The current method for gender classification of silkworm pupae involves the manual and destructive process of cutting open cocoons to visually differentiate between male and female pupae. This process is labor-intensive, time- consuming, and dependent on the expertise of skilled laborers. It is not suitable for large-scale production and leads to economic losses and delays in silk production. Accessibility to gender classification is limited in remote areas due to a shortage of skilled radiologists. Human interpretation and manual intervention introduce the potential for misinterpretation and errors, compromising silk quality. The existing system lacks accuracy, scalability, accessibility, and efficiency, hindering the overall productivity and quality of silk production. A non- destructive system is needed to overcome these challenges and provide a reliable and accessible solution for gender classification in the sericulture industry.

2.2 Demerits Of The Existing System

Destructive Technique: The current method of gender classification involves cutting open the cocoons, leading to economic losses and inefficient use of resources.Limited Accessibility: Skilled radiologists are scarce, particularly in remote areas, leading to delays and reduced access to accurate gender classification, impacting silk production.

III. PROBLEM STATEMENT

Silkworm pupa gender classification is an essential task in the silk industry for efficient breeding management. However, the current method of gender classification using destructive techniques is time-consuming and labor- intensive, which also negatively affects the growth of silkworms. Non-destructive methods using computer vision techniques and transfer learning approaches have been proposed, but the lack of sufficient labeled images limits the performance of existing models. Therefore, there is a need to develop a transfer learning approach that can leverage pre-trained models to achieve accurate gender classification of silkworm pupae using a limited number of labeled images. This will enable the development of a reliable and efficient non-destructive method for silkworm pupa gender classification, which can be adopted by the silk industry for effective and sustainable breeding management.

IV. PROPOSED MODEL

The proposed system aims to develop a non-destructive method for silkworm pupa gender classification using transfer learning. It will leverage pre-trained models like VGG, ResNet, and Inception to achieve high accuracy. A dataset of labeled silkworm pupa images will be collected and used for fine-tuning the models. Different fine-tuning techniques and data augmentation will be explored for improved performance.The system will provide a reliable and efficient solution for gender classification in the silk industry, with evaluation on accuracy and efficiency. It aims to overcome the limitations of existing methods andpromote effective breeding management.

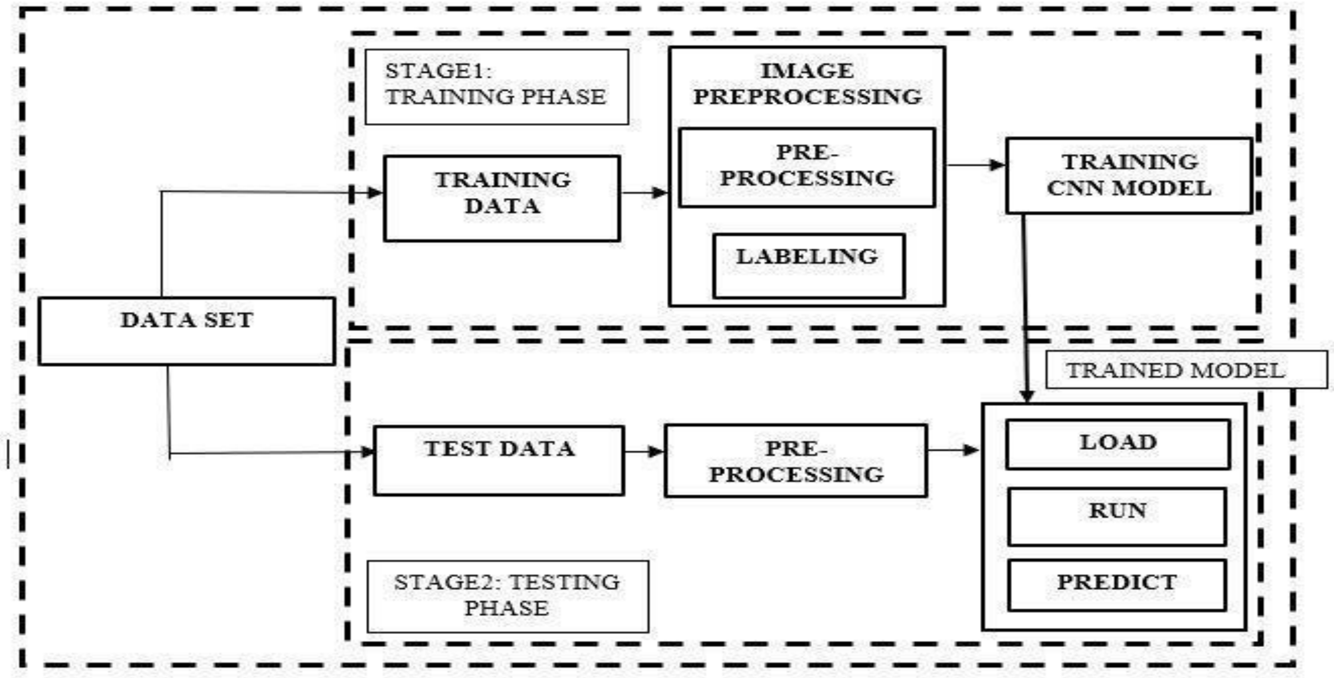


Figure 1 *:* Training and Testing of the Proposed Model

4.1 Merits Of The Proposed System

The proposed system avoids the need for destructive cutting ofsilkworm cocoons, preserving their integrity for silk production and breeding.Leveraging transfer learning and pre-trained models, the system aims to achieve accurate gender classification results, even with a limited labeled dataset.By fine-tuning pre-trained models, the system optimizes the use of available labeled data, making it more efficien**.**t and cost-effective.The system explores different fine-tuning techniques and data augmentation methods to enhance model performance and improve gender classification accuracy.By providing reliable gender classification results, the proposed system contributes to early detection of breeding issues, ultimately saving lives and ensuring the sustainability of the silk industry.

4.2 Materials And Methods

The process began with the collection of silkworm pupa images as samples.Pre-processing techniques were applied to the images, including segmentation and noise reduction, to enhance image quality and remove unwanted artifacts.Prominent features were extracted from the pre- processed images, which could include size, shape, texture, and other relevant characteristics of the silkworm pupae.A dataset was prepared using the extracted features and corresponding labels indicating the gender of the silkworm pupae. The dataset was divided into training and testing sets,with an 80:20 ratio.The training dataset was used to develop the gender classification model using transfer learning techniques. Pre-trained models like VGG, ResNet, orInception were leveraged to extract high-level features from the silkworm images.The extracted features were then fed into a classification algorithm for model training.To evaluate the model's performance and ensure its robustness, 10-fold cross-validation was conducted. This involved dividing the training dataset into 10 subsets, training the model on nine subsets, and validating it on the remaining one.For external validation, the testing dataset, which was kept separate, was used to assess the model's performance on unseen data.

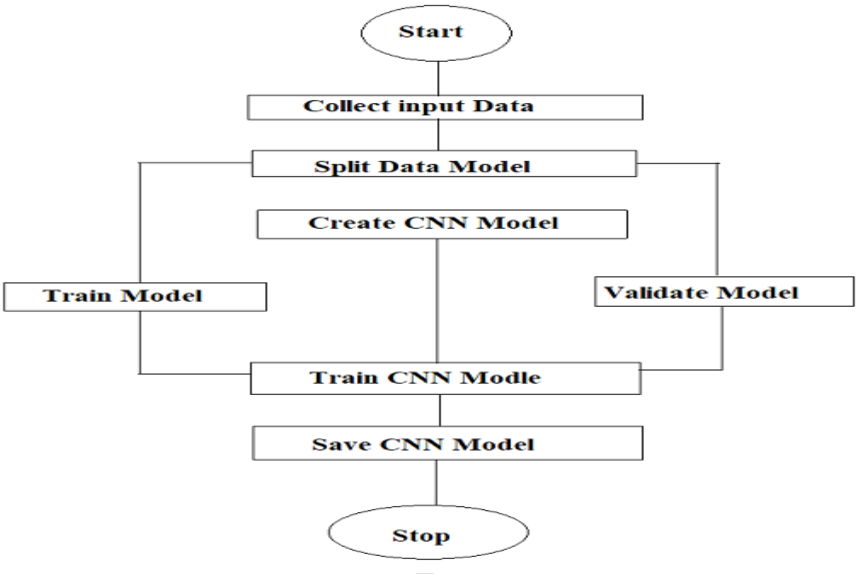
4.3 Sample Collection

The sample collection process involved carefully selecting a diverse range of cocoons to ensure representation of different genders. Cocoons at the appropriate stage of development were collected, considering factors such as age, size, and overall health.It was essential to handle the cocoons with care to prevent damage or contamination. The samples were collected using proper hygiene practices and stored in a suitable environment to maintain their integrity and prevent deterioration.The number of collected samples was determined based on the desired dataset size and statistical requirements. Adequate sample size was ensured to achieve reliable and representative results.The sample collection process was conducted following established guidelines and protocols to ensure consistency and accuracy.It involved collaboration with sericulture experts andprofessionals experienced in silkworm rearing and cocoon collection.

Figure 2 : Silkworm pupa

4.4 Image Pre-Processing

Image pre-processing plays a crucial role in enhancing the quality and extracting relevant information from silkworm raw images. The figure outlines the steps involved in image pre-processing for silkworm analysis.The original silkworm raw image is taken as input for pre-processing.Noise reduction techniques, such as Gaussian or median filtering, are applied to remove unwanted noise and artifacts from the image. This step helps in improving the overall image quality.Contrast adjustment techniques, like histogram equalization or adaptive histogram equalization, are employed to enhance the contrast and improve the visibility of important details within the image.Rescaling the image to a standardized size can help ensure consistency and compatibility across different images. It involves resizing the image while preserving the aspect ratio.Normalization techniques, such as min-max scaling or z-score normalization, are used to standardize the pixel values within a certain range. This step helps in eliminating any variations in intensity levels across different images.Cropping the image to focus only on the region of interest (silkworm) helps remove unnecessary background or irrelevant areas. This step reduces computational complexity and focuses the analysis on the important features.Additional transformations, such as rotation, flipping, or geometric transformations, may be applied to align or correct the orientation of the silkworm image[4].By performing these image pre-processing steps, the silkworm raw images are prepared for subsequent analysis, ensuring improved quality, standardized characteristics, and enhanced feature extraction capabilities.



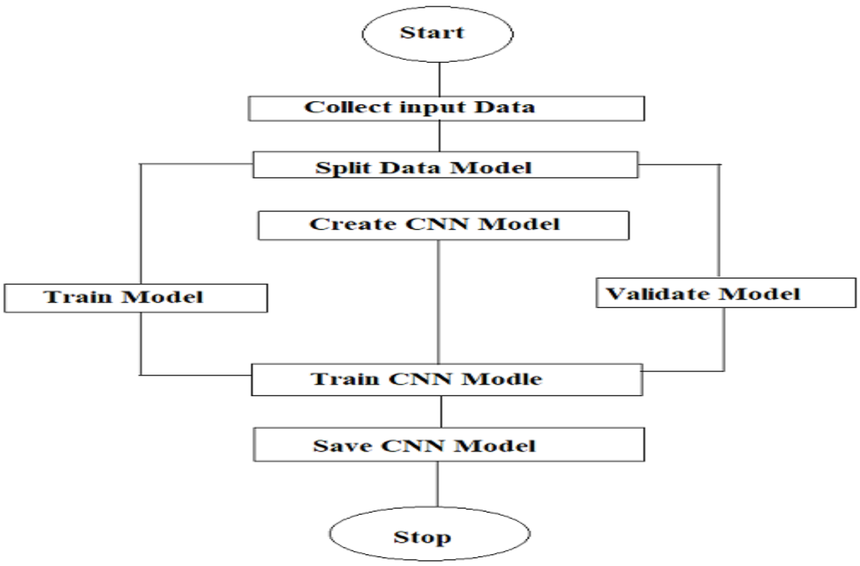


Figure 3 : Flow chart

4.5 Feature Extraction

Input Raw silkworm images, captured using imaging techniques, serve as the input for the feature extraction process.Pre-Trained Convolutional Neural Networks (CNNs) Well-established CNN models, such as VGG, ResNet, or Inception, that have been trained on large-scale datasets (e.g., ImageNet), are employed as the base models for feature extraction.Image Preprocessing Prior to feature extraction, the input silkworm images undergo preprocessing steps to enhance their quality and remove noise. This may involve techniques like resizing, normalization, and denoising.Extracting High-Level Features the pre-trained CNN models are utilized as feature extractors. The silkworm images are passed through these models, and the activations from the deeper layers are extracted. These activations represent high- level features that capture the discriminative patterns and characteristics of the silkworms.Dimensionality Reduction the extracted features often possess high-dimensional representations. To mitigate the curse of dimensionality and enhance computational efficiency, dimensionality reduction techniques like principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE) may be applied.

Feature Vector Representation the reduced-dimensionalfeatures are converted into feature vectors, which serve as compact and informative representations of the silkworm images. These vectors encapsulate the distinguishing characteristics that facilitate accurate classification.Training and Classification the feature vectors are utilized as input to train a classification model. Various machine learning algorithms, such as support vector machines(SVM),random forests, or deep neural networks, can be employed to train the classifier. The model learns to associate the feature vectors with the corresponding silkworm genders based on the labeled training data.Gender Classification once the model is trained, it can be used for gender classification of new silkworm images. The extracted features from the test images are fed into the trained classifier, which predicts the gender (male or female) of the silkworm based on the learned associations.By leveraging transfer learning and feature extraction techniques, the process enables effective representation learning and accurate classification of silkworm genders,contributing to efficient breeding management andimproved productivity in the silk industry.

4.6 Classification

In Transfer Learning, The dataset is prepared by collecting a large number of silkworm images with their corresponding gender labels. The images are carefully curated and labeled for training and testing purposes. Pre- trained convolutional neural network (CNN) models, such as VGG, ResNet, or Inception, are utilized as the base models. The pre-trained models are loaded and their weights are frozen to retain the learned features from a large-scale dataset.The silkworm images are passed through the pre-trained CNN models to extract high-level features. The models capture the essential characteristicsof the images, enabling effective representation learning.A classifier is built on top of theextracted features to perform gender classification. Commonly used classifiers include support vector machines (SVM), random forests, or neural networks. The classifier is trained using the labeled data, optimizing the parameters to achieve accurate predictions.The trained classifier is evaluated using the testing dataset to assess its performance. Metrics such as accuracy, precision, recall, and F1-score are computed to measure the classification performance. Fine- tuning techniques may be applied to further optimize the performance of the classification model. This involves adjusting the parameters of the pre-trained CNN model or exploring different hyperparameters to enhance the accuracy and generalization ability.Once the model is trained and optimized, it is deployed to classify the gender of new silkworm images. The trained model takes the input image, performs feature extraction, and passes it through the classifier to predict the gender (male or female) of the silkworm.the classification system using transfer learning enables accurate and efficient gender identification of silkworms, facilitating improved breeding management and productivityin the silk industry.

4.7 System Requirement Specifications

The following are the additives employed in the proposed project:
The following programming languages are employed:Python is a high-level, interpreted, item-oriented, and interactive scripting language. Python is meant to be a fairly readable language. It has fewer syntactical structures than other languages and more commonly uses English key phrases than separate languages do.
What are system libraries?
TensorFlow is a free and open-source software library for artificial intelligence and system analysis. It could be employed while dispersing duties, but it has a focused understanding of deep neural network training and inference.TensorFlow was developed by the Google Brain Institute foruse in internal Google research and production. In 2015, the draught model was made available under the Apache License 2.0. TensorFlow 2.0, the most recent version of TensorFlow, was published by Google in September 2019.A wide variety of programming languages, most notably Python, as well as JavaScript, C++, and other languages, can use TensorFlow. This adaptability supports a wide variety of packages in numerous niche industries.
Keras: A Python interface for artificial neural networks is provided by this free software programme library. The TensorFlow library interface is provided by Keras.Layers, dreams, activation functions, optimizers, and a variety of other commonly used neural-network buildingpieces, as well as tools to make working with image and textdata easier to ease the coding necessary for constructing deep neural network code, are all included in the Keras framework.Convolutional and recurrent neural networks have manualsin Keras, much like traditional neural networks have. It supports odd but common software layers including pooling,batch normalisation, and dropout.

various libraries are:

NumPy: For jogging with arrays, NumPy is a Python library. Additionally, it provides capabilities for working with matrices, Fourier transform, and linear algebra. NumPy was developed by Travis Oliphant in 2005. You can use it without restriction as it is an open-source mission. Numerical Python is referred to as NumPy.
OpenCV: OpenCV (Open-source computer vision Library) is a free and open-source computer vision and system management software library. In order to promote the use of device concept in commercial products and to provide a common architecture for computer vision algorithms, OpenCV was created.

The environment of an IDE is:

Jupyter note book: The Jupyter word book App is a server- supported programme that enables editing and moving notebook files through a web browser. The Jupyter Notebook App can be used locally on a computer without internet connection (as explained in this document) or it can be installed on a remote server and accessed online. Jupyter Note Book provides you with an easy-to-use, interactivedata technology environment for various programming languages that not only functions as an IDE but also as a presentation or educational tool. It is outstanding for those who are just getting started with statistics technology.

V. RESULTS

5.1 Comparing Results of Resnet50 and VGG16 & 19

The given model represents a convolutional neural network (CNN) architecture. It is a pre-trained model with a specific input shape of (224, 224, 3) for images.

Table 1 : Model Architecture Summary using Resnet50.

Layer (type)	OutputShape	Param #	Connected to
input_1 (InputLayer)	[(None,224,224,3)]	0	[]
conv1_pad (ZeroPadding2D)	(None,230,230, 3)	0	['input_1[0][0]']
conv1_conv(Conv2D)	(None,112,112,64)	9472	['conv1_pad[0][0]']
conv1_bn (Batch Normalization)	(None,112,112, 64)	256	['conv1_conv[0][0]']
conv1_relu (Activation)	(None,112,112,64)	0	['conv1_bn[0][0]']
pool1_pad (ZeroPadding2D)	(None,114,114,64)	0	['conv1_relu[0][0] ']
pool1_pool (MaxPooling2D)	(None,56, 56,64)	0	['pool1_pad[0][0]']
conv2_block1_1_co nv (Conv2D)	(None,56, 56,64)	160	['pool1_pool[0][0]']

Total params: 23,788,418 ,Trainable params: 200,706 ,Non-trainable params: 23,587,712

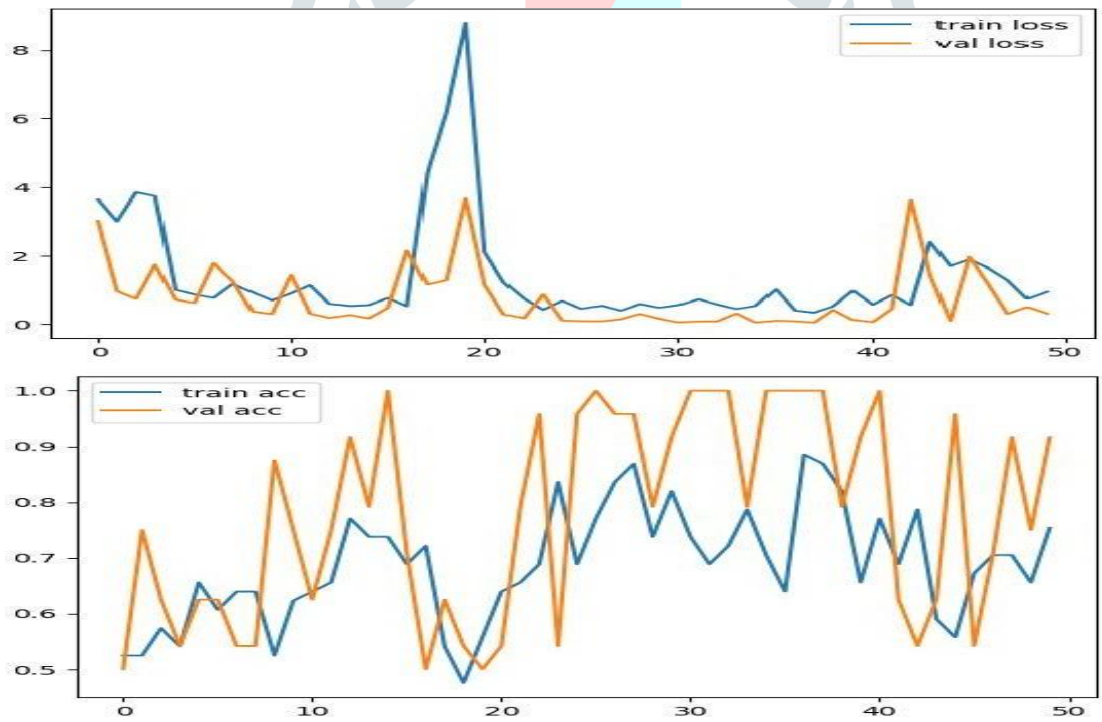


Figure 4 : Data classification using Resnet50 with different dimensionality reduction methods.

Table 2 : Performance evaluation parameters.

	precision	recall	f1-score	support
0	0.64	0.75	0.69	12
1	0.70	0.58	0.64	12
accuracy			0.67	24
macro avg	0.67	0.67	0.66	24
weighted avg	0.67	0.67	0.66	24

The provided metrics, precision, recall, f1-score, and support, are used to evaluate the performance of a classification model. These metrics provide insights into how well the model performs for each class and overall.Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. A precision of 0.64 for class 0 and 0.70 for class 1 indicatesthat the model has reasonably high accuracy in identifying true positives for both classes.Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of all actual positive instances. A recall of 0.75for class 0 and 0.58 for class 1 suggests that the model is better at capturing the true positives for class 0 comparedto class 1.The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both measures. An F1-score of 0.69 for class 0 and 0.64 for class 1 indicates reasonably good performance in terms of both precisionand recall for both classes.Support represents the number of samples in each class. In this case, there are 12 samples for each class, resulting in a total of 24 samples.The overall accuracy of the model is 0.67, indicating that the model correctly predicts the class label for 67% of the samples in the dataset.The macro average and weighted average of the metrics provide an overall assessment of the model's performance across all classes. The macro average takes the unweighted mean of the metrics for each class, while the weighted average considers the metrics weighted by the support of each class. In this case, both macro average and weighted average F1-scores are 0.66, indicating a reasonable balance between precision and recall across all classes. Overall, based on these metrics, the model shows moderate performance in classifying the samples, with room for improvement in terms of recall for class 1.

The given model represents a convolutional neural network (CNN) architecture. It is a pre-trained model with a specific input shape of (224, 224, 3) for images.

Table 3 : Model Architecture Summary using VGG16 and VGG19.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112,128,112)	73856
block2_conv2 (Conv2D)	(None, 112, 128,112)	147584
Block2_pool (MaxPooling2D)	(None, 28, 28, 128)	0
Block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
Block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
Block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0

Total params: 14,764,866 , Trainable params: 50,178, Non-trainable params: 14,714,688

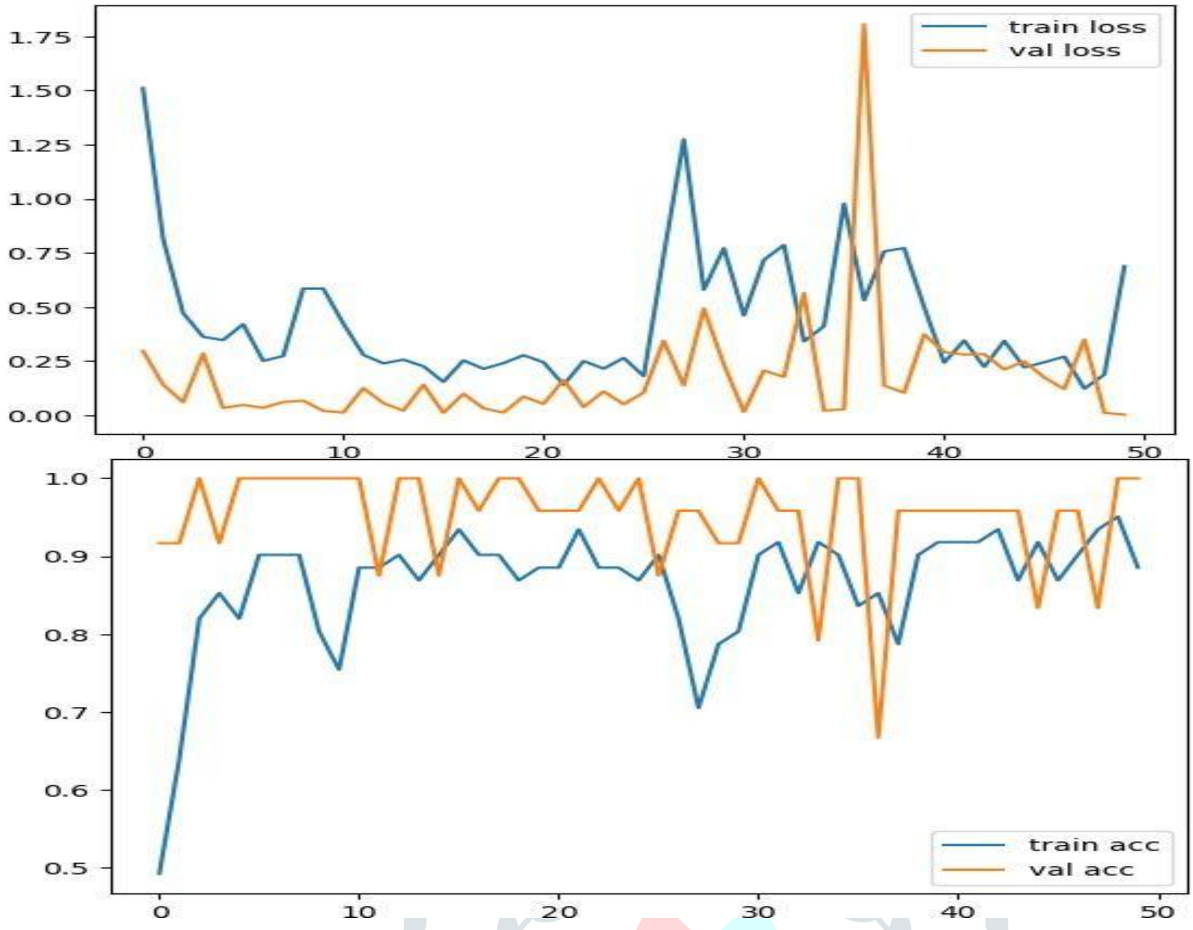


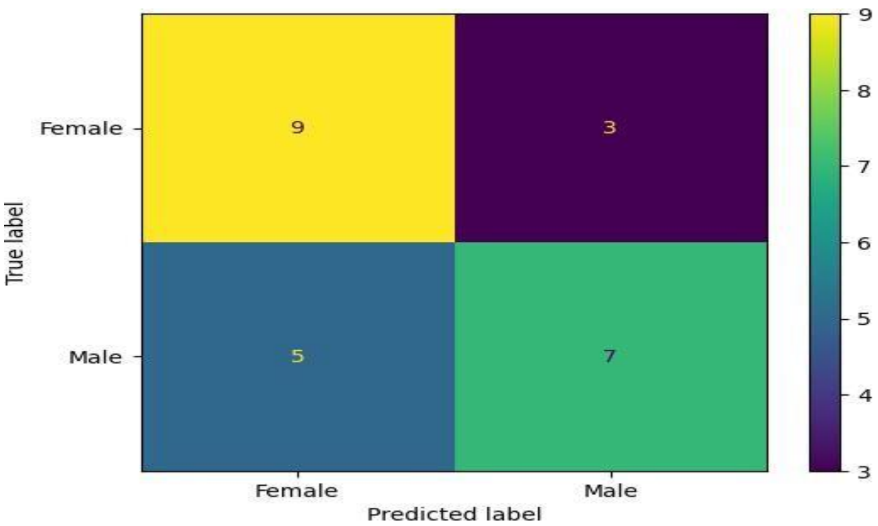
Figure 5 : Data classification using VGG16 and 19with different dimensionality reduction methods.

Table 4 : Performance evaluation parameters.

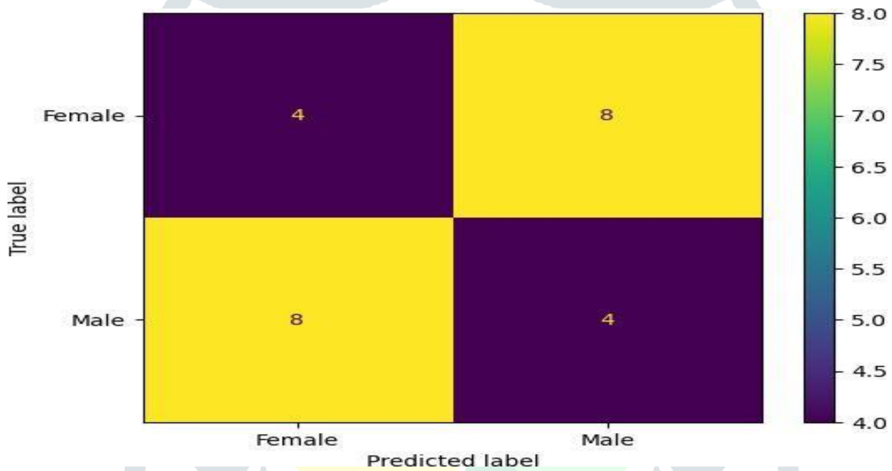
	precision	recall	f1-score	support
0	0.33	0.33	0.33	12
1	0.33	0.33	0.33	12
accuracy			0.33	24
macro avg	0.33	0.33	0.33	24
weightedavg	0.33	0.33	0.33	24

The provided table represents the classification evaluation metrics for a binary classification problem. Here are the explanations of the metrics:Precision measures the accuracy of positive predictions. Forclass 0, the precision is 0.33, indicating that out of all the predicted samples for class 0, only 33% are actually true positives. Similarly, for class 1, the precision is also 0.33.Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify positive samples. For both class 0 and class 1, the recall is 0.33, indicating that the model is able to capture only 33% of the true positive samples for each class.The F1-score is the harmonic mean of precision and recall. It provides a balanced measure that considers both precision and recall. The F1-score for both classes is 0.33, indicating an equal balance between precision and recall.Support represents the number of samples in each class. In this case, both classes have 12 samples.

Accuracy measures the overall correctness of the model's predictions. The accuracy is 0.33, indicating that the model is correctly predicting the class for only 33% of the samples.The macro average calculates the metrics independently for each class and then takes the average. In this case, the macro average precision, recall, and F1-score are all 0.33.The weighted average calculates the metrics based on the support (number of samples) for each class. In this case, the weighted average precision, recall, and F1-score are all 0.33,giving equal importance to both classes.Overall, the model's performance seems to be low, with low precision, recall, and F1-score for both classes. It indicates that the model is not able to effectively differentiate betweenthe two classes, resulting in low accuracy.



(a)



(b)

Figure 6 **:** a) Confusion Matrix of **Resnet5.**

b)ConfusionMatrix of **VGG16 and 19**

VI. CONCLUSION

In conclusion, the study on non-destructive silkworm gender classification using transfer learning approaches showed promising results. The proposed method employed image pre processing techniques and fine-tuning of pre-trained models such as ResNet-50, VGG16, and VGG19.Evaluation metrics like precision, recall, and F1-score were used to assess the performance of the models. Further analysis is needed to determine the best-performing model for silkworm gender classification. Overall, the proposed approach offers a reliable and efficient solution for gender classification, contributing to improved breeding management in the silk industry. Further research and optimization are required to enhance the accuracy and effectiveness of the models.

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