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A Machine Learning approach to Silkworm pupae gender identification

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ABSTRACT

Silkworm production is an important industry worldwide, particularly in regions where silk production is a significant economic activity. The goal is to quickly and accurately identify the gender of silkworm pupae. Visual classification methods of silkworm gender are time-consuming and leading to errors, it reduces productivity. The objective is to develop a software-based solution for gender classification of silkworm pupae using machine learning technique. A machine learning approach of classifying silkworm pupae gender is proposed using a dataset of 950 images. Before getting into transfer learning the dataset was tested with different edge detection techniques like Canny, Sobel and Prewitt to identify the gender based on edges. But it depends on image quality, rotation and reference image. Then the dataset is tried with a feature detection method like Oriented FAST and Rotated BRIEF (ORB) but it is a rotation variant and sensitivity to noise. The dataset is pre-processed and augmented to produce 3000 images in order to improve the accuracy. Conventional Neural Network (CNN) will automatically learn hierarchical features from raw data. Next, a 4:1 split of the dataset is made into training and testing sets. Model training begins with feature extraction using CNN architectures such as MobileNetV2 and ends with the plotting of model evaluation metrics. The accuracy obtained from the MobileNetV2 architecture is 95%.

KEYWORDS

Convolutional Neural Network (CNN); Edge detection; Oriented Fast and Rotated BRIEF (ORB); Image augmentation; Machine learning; MobileNetV2; Silkworm pupae; Transfer learning,

1. INTRODUCTION

Sericulture was first used in China and has been around for more than 5,000 years. Eventually, sericulture spread across other parts of Asia, then to Europe and other continents. Raising silkworms particularly the Bombyx mori [9] species to produce the highly prized natural Fiber known as silk is the meticulous and age-old process of sericulture. This complex enterprise consists of several carefully monitored processes, starting with the production of mulberry trees, which are the main food source for silkworm [22]. Due to their extraordinary sensitivity to temperature, humidity, and light fluctuations, these small larvae are maintained under controlled conditions with constant observation of their development. For around 25 to 30 days, silkworms feed only on mulberry leaves, and then they use the silk they produce to cocoon themselves. Once the cocoons are harvested, they are gathered with care, and usually the pupa inside is killed to avoid damaging the silk thread when the cocoon opens. The silk thread is converted into a vast variety of beautiful fabrics, from clothing to accessories and home furnishings, by boiling, reeling, spinning, and weaving. Silkworms are the larval form of the silk moth, not regular worms. Because the production of silk is central to their life cycle, they are an essential part of the sericulture sector.

Early manual classification is used for gender classification of silkworm pupae. But it is time consuming, reduces productivity and leads to errors. Normalized cross correlation (NCC) based pattern matching is used for silkworm sex identification [21]. But it requires a large dataset of labelled silkworm pupae. For quick gender identification fault tolerant optical penetration is used [7], but environment conditions affect the accuracy and equipment cost is high. Image processing and Support Vector Machine (SVM) algorithm is used for automatic silkworm pupa gender classification [17]. In this method multiple sensors are used, but combining data from multiple sensors can be complicated. Automatic exposure correction algorithm is used for classification [24], implementation of this algorithm is difficult. Ensemble learning technique with X-ray imaging is used for silkworm pupa gender classification [25], but it requires a large dataset.

To overcome these problems automated silkworm pupa gender classification using MobileNetV2 is implemented. The proposed method will classify the silkworm pupa into male, female and defects. The dataset contains 415 male images, 431 female images and 104 defects images. The proposed method uses CNN [6] for feature extraction. CNN architectures like MobileNetV2 can be used as a feature extractor for training the model.

1.1 Different Stages of Silkworm:

1) Egg stage: (Figure 1a) The life cycle of a silkworm begins with the laying of eggs by a female moth. They take about 10-14 days to hatch, depending on temperature and other environmental factors.
2) Larva stage: (Figure 1b) After the eggs hatch, the young silkworms emerge as larvae. During this stage, the silkworms are voracious eaters and primarily feed on mulberry leaves. The larval stage is characterized by rapid growth, and it typically lasts for about 4-6 weeks.

3) Pupa stage (Cocoon Formation): (Figure 1c) At the end of the larval stage, the silkworms stop eating. Silkworms wrap themselves in these silk threads to create protective cocoons. Inside the cocoon, the silkworm undergoes metamorphosis, transforming into a pupa. This stage lasts for approximately 2-3 weeks.

4) Adult stage (Moth): (Figure 1d) Once the transformation inside the cocoon is complete, the pupa inside the cocoon undergoes further changes and eventually emerges as an adult moth. The adult moths have a very short lifespan, usually living only a few days.

a) b) c) d)

Fig. 1 a) Silkworm egg b) Larva c) Pupae d) Moth

2. LITERATURE REVIEW

Identifying the gender of silkworm pupae is crucial in sericulture for breeding purposes. Traditionally, manual methods like examining the genitalia or size differences have been used. Traditional methods often involve visual inspection based on morphological differences between male and female pupae. These differences may include size, colour, and abdominal shape. One common approach is observing the size and shape of the pupae, as female pupae tend to be larger and more rounded compared to males. Another traditional method involves examining the colour and texture of the pupal skin, as females typically have smoother and lighter-coloured skin compared to males. These methods can be subjective and prone to errors. For accurately determining the gender of silkworm pupae through X-ray imaging and ensemble learning techniques [25]. The ensemble of machine learning models is trained on the extracted features to classify pupae into male or female categories.

The combination of multiple models helps improve the accuracy and robustness of the classification [23]. Ensemble model for gender classification requires a large and diverse dataset of silkworm pupa X-ray images. In [24], the author proposed an algorithm to address exposure- related Challenges when classifying the gender of silkworm pupae in an online, real-time setting. For silkworm pupae gender classification automatic exposure correction algorithm is used. Developing and implementing an automatic exposure correction algorithm can be complex. The development of a comprehensive system for automating the gender classification of silkworm cocoons based on the data gathered from the sensors and processed through the SVM classifier [17]. This may include colour analysis, texture analysis and shape analysis. Combining data from multiple sensors and processing them coherently can be complicated. For rapidly and non-invasively identifying the gender of living silkworm pupae. The key approach involves employing near-infrared spectroscopy to analyse the unique chemical compositions or spectral patterns associated with male and female pupae. Implementing near-infrared spectroscopy [12] (NIRS) systems can be expensive due to the cost of the spectrometer and associated hardware.

To improve the reliability and robustness of gender identification in silkworms using optical penetration techniques [8]. The key idea is to design a system that can withstand and compensate for potential errors or challenges that may arise during the identification process. The effectiveness of optical-penetration-based systems [7] can be sensitive to environmental conditions, such as lighting and temperature. In [21], advanced imaging and pattern recognition techniques to develop a non-invasive and efficient method for determining the gender of silkworm pupae. To develop a pattern matching model, a large dataset of labelled silkworm pupae is needed. An innovative approach to enhance the accuracy and efficiency of gender determination in silkworms using advanced imaging technologies and machine learning algorithms to focus on specific anatomical areas or regions of interest (ROIs) [19], such as genitalia or gonads, during the gender identification process.

Based on the literature survey mainly focuses on non-destructive gender classification [20] of silkworm pupae using X-ray imaging and ensemble learning techniques, it doesn't discuss the potential scalability and practicality of implementing this method in large-scale sericulture operations. The automatic gender classification of silkworm cocoons using sensor data and SVM classification [17]. However, just the potential challenges related to sensor accuracy, data collection, and real-world implementation. While the existing methods present an innovative method for non-invasive gender identification in living silkworm pupae using near-infrared spectroscopy. Accuracy of image analysis techniques relies on the quality of the images captured. Other factors of silkworm pupae include size, shape and texture making it challenging to achieve the consistent and accurate image analysis results. Machine learning algorithms like SVM and CNN [3], [13] are often utilized for classification [1]. These methods not only improve accuracy but also significantly reduce the time and effort required for manual analysis.

Figure 2 shows the publications that deal with machine learning methods for silkworm pupa gender classification.

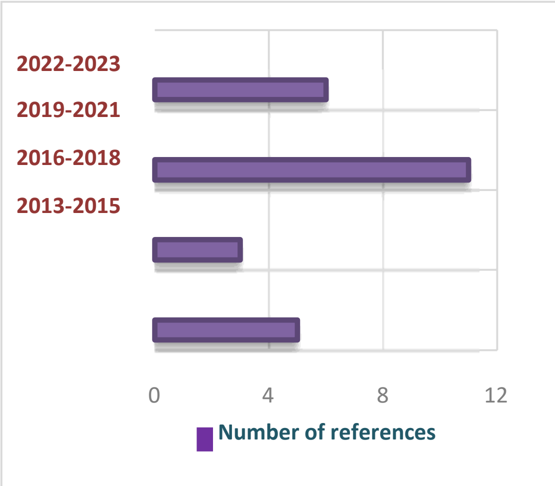


Fig. 2 Publications year for pupae under image classification

3. PROPOSED METHOD

Gender classification of Silkworm pupae is crucial to maximize silk production. The proposed method for silkworm pupae gender classification will predict the given input image from webcam into male, female and defects. First image will be collected, and a dataset will be generated. It contains 950 images which includes 415 male, 431 female and 104 defects images. Before going to transfer learning, the dataset will be tested with different edge detection techniques like Canny, Sobel and Prewitt. Comparing three techniques, Canny performs well in detection of low edges. But results will vary with image quality, image augmentation and reference image. Then the dataset is tried with feature detection techniques like ORB which maps the similar feature in the input image with the given image, but it is rotation variant at extreme point and more sensitive to noise.

Figure 3 shows the workflow of the proposed methodology. It uses CNN architectures for feature extraction because CNN will automatically learn hierarchical features from raw data. Then it undergoes image augmentation such as different angle rotations so the dataset will be improved into 3000 images. After pre-processing it performs resize to increase the prediction accuracy.

The dataset is labelled and divided into training and testing sets. It will be split into testing and training in the ratio of 4:1. MobileNetV2 can be used as a feature extractor for training the model. Trained the model using a training dataset and tested the training model using testing dataset. Then plot the evaluation metrics. When compared to manual classification, these techniques are effective. They are ideal for both academic and precise. By ensuring that the proper individuals are chosen for mating and silk production, these techniques can also assist decrease errors and enhance breeding programs.

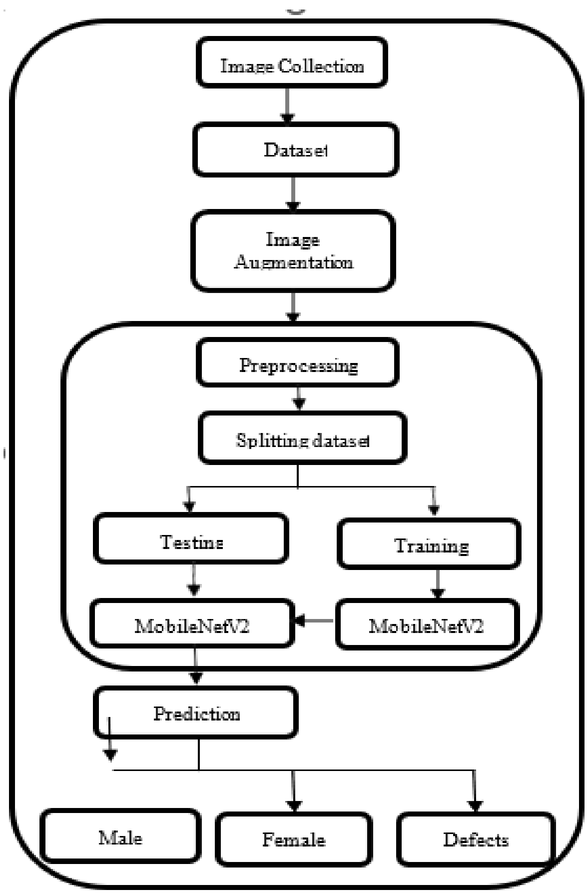


Fig. 3 Flowchart of proposed methodology

3.1 Edge Detection:

Edge detection is an image processing approach that finds discontinuities, or sudden changes in image brightness, at specific points in a digital image. Two 3 x 3 convolution masks are used by the Sobel edge detector; one estimates gradients in the x direction, and the other in the y direction. Because of its extreme sensitivity, the Sobel highlights noise in pictures as edges. The Prewitt operator can identify two different kinds of edges. One is vertical edges that operate along the y-axis and another one is horizontal edges that operate along the x-axis. Canny edge detection is an image processing technique that involves convolving the image with a Gaussian filter to reduce noise, applying gradient operators to highlight edges, suppressing non-maximum values to refine the edges, and employing hysteresis to trace and link edges based on defined thresholds.

Figure 4 a, b and c represent the Canny, Sobel and Prewitt edge detected image of silkworm pupa. From the above methods Canny edge detection provides high edge quality.

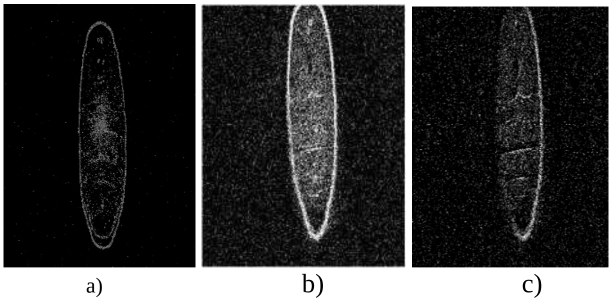


Fig. 4 a) Canny edge detection b) Sobel edge detection c) Prewitt edge detection

3.2 Feature Detection:

Oriented FAST and rotated BRIEF (ORB) is a computer vision algorithm designed for feature detection and description. It integrates the FAST key point detector, leveraging pixel intensity comparisons for rapid corner identification. The BRIEF descriptor is then applied to encode distinctive information from these key points into binary strings. To enhance robustness, ORB introduces orientation assignment, ensuring rotational invariance. Feature points are important for various computer vision tasks, such as image matching, object recognition [4], and tracking. It can detect and describe features across different scales and orientations, which is important for handling objects at different sizes and orientations in images. The dataset is tested with a given input image compared with reference images, it will vary based on reference image and orientation.

Figure 5 represents the feature detection of female pupa image with ORB detector. The X and Y axis of the image represents the dimensions. It has disadvantages in terms of feature distinctiveness and robustness in complex scenes or with extreme scale and orientation changes.

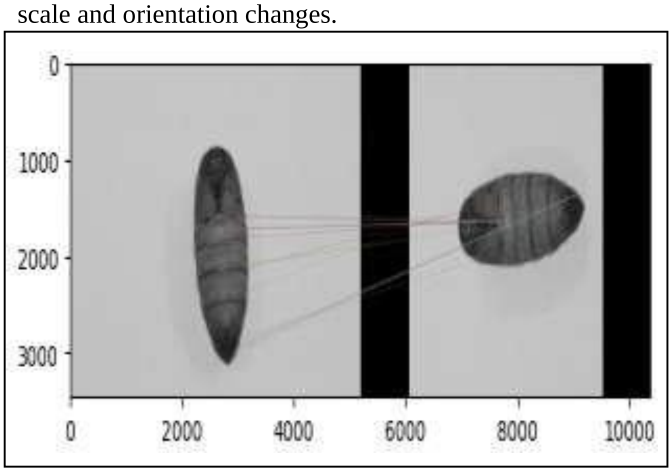


Fig. 5 Feature detection with ORB

3.3 Transfer Learning:

Transfer learning [5], [11] is a method used in image processing where pre-trained deep learning models are utilized as a basis to tackle image-related tasks [14]. Mobile Net is a family of convolutional neural network (CNN) architectures developed to provide efficient and lightweight deep learning solutions for mobile and embedded devices. These models were created to offer effective and less computationally intensive solutions for computer vision problems like image classification, object recognition, image segmentation and more. In applications like mobile apps, edge devices, and real-time systems, where both accuracy and model size/complexity are crucial, Mobile Net models have gained popularity. The higher performance to model size trade-off provided by MobileNetV2 [2], [16], [18] makes it a good choice for devices with limited resources.

Figure 6. shows the two stride blocks in Mobile Net architecture. The 53 layers of MobileNetV2 [15] include a variety of layers, including batch normalization, depth wise separable convolutions, and activation functions, which together allow for effective feature extraction and classification for computer vision tasks.

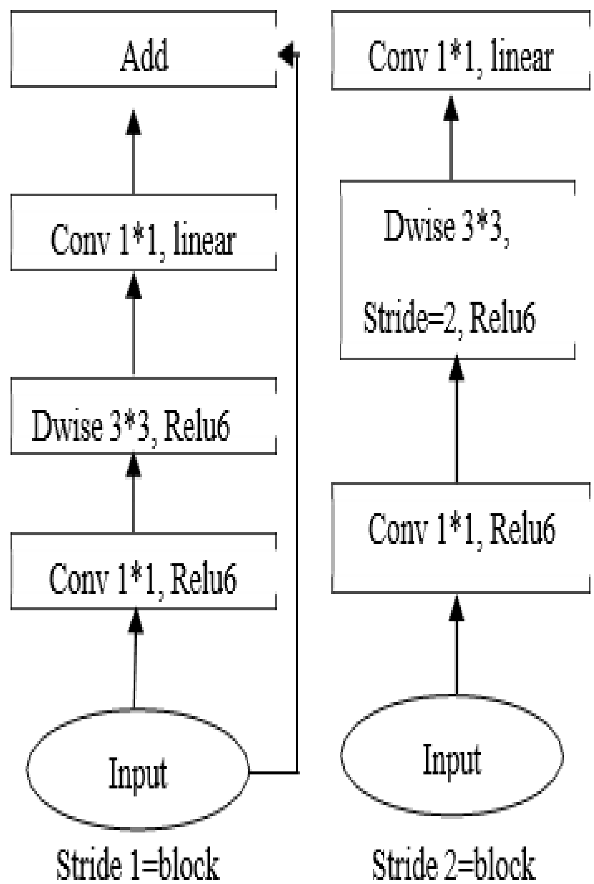


Fig. 6 MobileNetV2 architecture stride block

Table.1 represents the layers in the MobileNetV2 architecture. In the below table t, n, c, and s represent the expansion factor, repeated times of a sequence of 1 or more identical layers, output channels and stride respectively. The first layer of each sequence has a stride s and all others use stride 1. All convolutions follow a 3 x 3 kernel.

Table. 1 MobileNetV2 layers

Input	Operator	t	c	n	s
224 x 3	conv2d	-	32	1	2
112 x 32	bottleneck	1	16	1	1
112 x 16	bottleneck	6	24	2	2
56 x 24	bottleneck	6	32	3	2
28 x 32	bottleneck	6	64	4	2
14 x 64	bottleneck	6	96	3	1
14 x 96	bottleneck	6	160	3	2
7 x 160	bottleneck	6	320	1	1
7 x 320	conv2d 1x 1	-	1280	1	1
7 x 1280	avg pool 7 x 7	-	-	1	-
1 x 1 x 1280	conv2d 1x 1	-	k	-	

3.4 Data Collection:

1) Image Collection:

The process of gathering and compiling a dataset of images for various uses, such as computer vision, machine learning, research documentation and analysis, is referred to as image collection. Internet, smartphones, digital cameras, already-existing databases, sensor data, surveys, scanned photos, and other imaging tools are only a few examples of sources.

Figure 7 shows the images of male pupae, female pupae and defect pupae are collected from the Sericulture department of Erode.

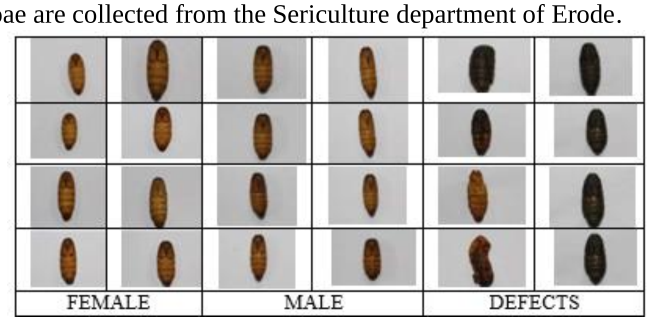


Fig. 7 Collection of male, female and defected pupa

2) Dataset of Pupae:

A critical step in the machine learning model training process is dataset preparation. To train, validate, and test the model, it is needed to gather, clean, and arrange the data. To make sure the model works well and generalizes successfully, it is essential to prepare the dataset properly. The dataset gathered is 950 pupae images which includes male, female and defects.

Figure 8 (a-c) represents the male, female and defect pupae collected.

a) *b)* *c)*

Fig. 8 a) Female pupa b) Male pupa c) Defect pupa

Figure 9 shows the distribution of the dataset of pupae collected from the sericulture centre. It consists of 415 male pupa images, 431 female pupa images and 104 defective pupae images.

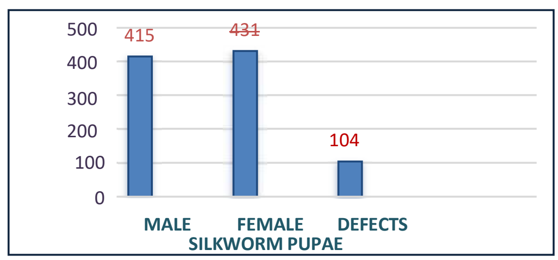


Fig. 9 Distribution of dataset

3) Image Augmentation:

To artificially expand the amount and diversity of an image dataset, the technique of image augmentation is employed in computer vision and machine learning. Image augmentation, which alters the original images in various ways, aids machine learning models in performing better overall and in tasks like object identification, and segmentation, as well as in tasks like image categorization and object detection. Image augmentations techniques include rotation, flip, noise addition, scaling and cropping.

a) b) c) d)

Fig. 10 a) 0-degree rotation b) 90-degree rotation
c) 180-degree rotation d) 270-degree rotation

The generated dataset will undergo different angular rotations to expand the dataset and to train the model to predict the silkworm pupae in different angles. After image augmentation the expanded dataset will be 3000 images. It improves the model's robustness.

Figure 10 (a-d) represents the different orientations of the original image. The first image represents the original image of female pupae then it undergoes various orientations like 90-degree, 180 degree and 270 degrees.

4) Pre-processing:

Data pre-processing is a next stage in the pipeline for data analysis and machine learning. It involves a series of tasks to clean, transform, and organize raw data into a format suitable for analysis or modelling. Data accuracy, consistency, and relevance to the research or application depend on proper data pre-processing. It involves scaling or normalizing features to ensure that they are on a common scale. It resizes the image to a new size of 224x224 pixels using the resize method. Mobile Net, like many other CNNs, benefits from having input data that is normalized. The model converges more quickly and is less sensitive to the scale of input data due to normalization. Additionally, it can aid in avoiding gradients that vanish or explode during back- propagation. Dataset is labelled and divided into training and test sets.

Figure 11 represents the original image before pre-processing and Figure 12 shows the pre-processed image of 224x224 pixels.

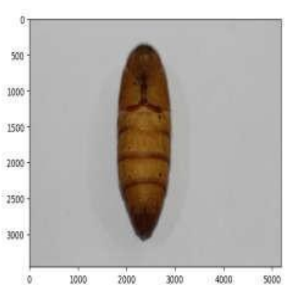


Fig. 11 Original image

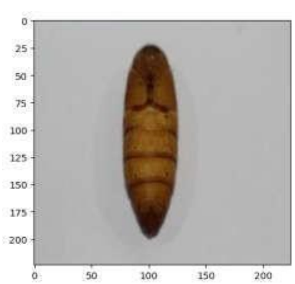


Fig. 12 Resized image

5) Training the Model:

The training dataset is used to train the CNN model. By using frameworks like TensorFlow, PyTorch or Keras to build and train the model. These frameworks provide pre-trained versions of MobileNetV2. The pre-trained MobileNetV2 model should be loaded. It can recognize a variety of features because they have already been trained on large image datasets like ImageNet. Freeze some of the initial layers and modify only the top layers of the pre-trained model for the desired number of classes. There are 2400 images in the training dataset. It is necessary to set evaluation metrics, choose an optimizer (Adam), and define a loss function, such as binary cross entropy.

6) Testing:

Test the model's performance on the test dataset to get an accurate measure of its gender classification accuracy. To assess its performance, it is essential to test the model. The testing dataset contains 600 images. Ensure that the test set contains completely new data that the model has not seen during training. Load the previously trained models then use the loaded model to make predictions on the test dataset.

7) Evaluation Metrics:

In several disciplines, including machine learning, data analysis, information retrieval, and others, evaluation metrics are used for evaluating the effectiveness of models, systems, algorithms, or processes. These metrics offer a measurable approach to assess the value and efficiency of a certain model or system in dealing with a particular issue. It includes precision, recall, accuracy and F1 score. Using the confusion matrix calculated the evaluation metrics to assess the performance and effectiveness of machine learning models as in (1), (2), (3) and (4). The proposed model MobileNetV2 performance was evaluated using the below metrics.

$$\text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$\text{Precision} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP}{TP+FP} \quad (2)$$

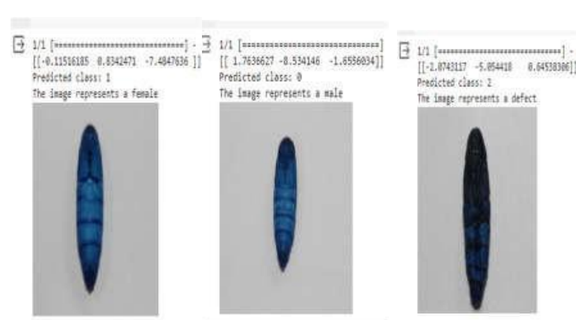
$$\text{Recall} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP}{TP+FN} \quad (3)$$

$$\text{F1 Score} = \frac{2*precision*Recall}{precision+Recall} \quad (4)$$

4. RESULT AND DISCUSSION

The gender prediction is done with the help of the MobileNetv2 architecture. The training and testing accuracy was attached below along with the Model Loss and Model accuracy graph was plotted. The Confusion matrix, training loss, accuracy, testing loss, accuracy, epochs and model graph of testing and training accuracy of both the architecture was plotted.

Figure 13 shows prediction of the silkworm pupae whether it is male, female or defects by MobileNetV2 architecture.



a) Female pupae b) Male pupae c) Defected pupae

Fig. 13 MobileNetV2 results

	Predicted 0	Predicted 1	Predicted 2
Actual 0	268	15	1
Actual 1	12	286	0
Actual 2	1	0	17

Fig. 14 Confusion matrix (MobileNetV2 architecture)

Figure 14 represents the Confusion matrix. Confusion matrix is the visualization of the algorithm used for measuring the prediction value, accuracy and F1 score of the model. Class 0, 1 and 2 represents male, female and defect pupae.

The accuracy of MobileNetV2 architecture was calculated from correct and all predictions of three classes as in (5).

$$\text{Accuracy} = \frac{correcct\ predictions}{All\ predictions}$$

$$= \frac{268+286+17}{268+15+1+12+286+1+17}$$

$$= 0.95 \qquad (5)$$

Table 2 implies the calculation of total precision, recall and F1 score of MobileNetV2 architecture. First it will calculate precision, recall and F1 score for separate classes and take an average of three to find total value.

Table. 2 Calculation of precision, recall and F1 score of MobileNetV2 architecture

Class	Precision	Recall	F1 Score
0	0.94	0.95	0.94
1	0.95	0.95	0.95
2	0.94	0.94	0.94
Total	0.94	0.95	0.94

Figure 15 implies the model accuracy graph between the training accuracy and testing accuracy obtained from the MobileNetV2 architecture. The blue line indicates the training accuracy which will increase with the number of epochs and similarly the orange line indicates the testing accuracy of the MobileNetV2 model.

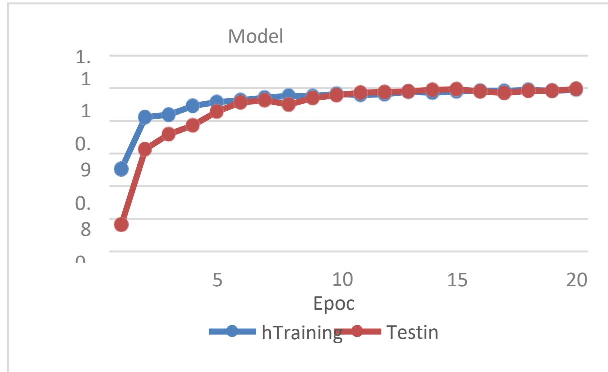


Fig. 15 Model Accuracy Graph

Figure 16 implies the model loss graph between the training loss and testing loss is obtained from the MobileNetV2 architecture. The blue line indicates the training loss which will decrease with the number of epochs and similarly the orange line indicates the testing loss of the MobileNetV2 model.

Fig. 16 Model Loss Graph

Table 3 implies the MobileNetV2 architecture. These values are derived with the help of a confusion matrix, the accuracy of MobileNetV2 architecture is 95%.

Table. 3 Table of MobileNetV2 architecture

C Matrix	MobileNetV2
Precision	0.94
Recall	0.95
F1 Score	0.94
Accuracy	0.95

MobileNetV2 achieved high accuracy through its efficient use of depth wise separable convolutions, inverted residuals, and linear bottlenecks, optimizing the balance between model complexity and computational efficiency.

5. CONCLUSION AND FUTURE WORK

Identifying minute differences from identical images is quite difficult task in visual inspection method. Traditional visual classification methods can be time-consuming and prone to errors, the software-based solution offers a more efficient and accurate solution for identifying silkworm gender. Pre-processing and augmenting the dataset enhance model performance by optimizing data quality. The use of MobileNetV2 architecture enhances the efficiency of the classification process. Classify the silkworm pupae as male, female and defects by using transfer learning methods like MobileNetV2. In MobileNetV2 architecture the accuracy obtained is 95%. In the Proposed model, the evaluation includes Recall, Precision, F1 score, and Accuracy. Gender classification of silkworm pupae has been done with the help of MobileNetV2 architecture.

At present, only desktop or laptop computers can predict the gender of silkworm pupae. Therefore, future work will involve creating an embedded hardware with an integrated camera, vibration motor, conveyer belt, raspberry pi and tray to automatically categorize silkworm pupae by gender and identify those that are healthy or diseased. Based on accuracy MobileNetV2 model will be used to help develop an Artificial Intelligence (AI)-based hardware system for the gender classification of silkworm pupae and it will reduce the manpower.

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