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DETECTION OF BATS IN AGRICULTURE FARMS USING MODIFIED RESNET50V2 DEEP LEARNING MODEL

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Abstract
Farmers are actively exploring ways to enhance crop yield in order to meet the growing global demand for food, and minimizing damage caused by bats is one approach to achieve this goal. Bats can feed on various crops, causing significant economic losses for farmers, especially in orchards and vineyards. They can carry diseases, such as pseudorabies and rabies, that can affect both crops and livestock. This paper presents the use of computer vision and machine learning algorithms to detect bats in images captured in agricultural areas. This technology typically uses cameras equipped visible light sensors to capture images of bats in the farms. The resulting data can provide farmers and other stakeholders with information about bat activity in their fields, including the number of bats, their flight patterns, and the times of day when they are most active. The proposed framework uses a modified ResNet50V2 deep learning model for image classification. The proposed model identifies bats in images by classifying farm images into bat and non-bat images. The proposed model classifies the bat images with an accuracy of 97.8%.

Keywords: bat detection, image classification, Resnet50V2, agriculture, crop yield.

I. Introduction
Agriculture is likely to see a significant productivity boost as a direct result of the rising demand for food. Bats can pose several problems in agriculture:

1. Crop damage: Bats can feed on crops, especially in orchards and vineyards, causing significant economic losses for farmers.
2. Disease transmission: Bats can carry diseases, such as pseudorabies and rabies, that can affect both crops and livestock.
3. Increased pest populations: When bats are disrupted or killed, their natural pest control services are lost, leading to an increase in insect pest populations that can harm crops.
4. Fear and misconceptions: Many people are afraid of bats, and misconceptions about these animals can lead to negative attitudes toward bats and their conservation.

To mitigate these problems, farmers may use exclusion methods, such as netting, to protect their crops, and educate themselves and their communities about the benefits of bats in agriculture. Additionally, promoting sustainable agricultural practices that support bat populations can help to ensure the continued positive impact of bats on agriculture.
Several different methods have been offered as potential ways of determining whether or not bats are inhabiting agriculture farms [4-5]. The detection of acoustic signals is the focus of one strategy, which tries to establish the existence of bats. Bats communicate with their environment by sending out acoustic pulses and listening to the reflections of those pulses [6-7]. Over the course of the last several decades, a lot of research has been done on the subject of monitoring bats using acoustic signals. In spite of the fact that commercial bat detectors are available, getting reliable results from them calls for meticulous gadget setup and operators with plenty of expertise. Due to the high cost associated with these kinds of bat detectors, their use and usage by owners of infrastructure is often restricted. Even when bat detectors are used properly, the findings of bat identification might still be questioned due to inconsistencies between various acoustic signal processing software applications [8].

Visual examination is yet another method that may be used to determine whether or not bats are present on agriculture lands. In the subject of computer visual recognition, image classification is one of the essential problems, and it is also one of the tasks that has established substantial successes over the previous decade. Bats can cause damage to the fruits in horticulture. Some species of bats are known to feed on fruit, and when they do so, they may leave behind marks or wounds that can make the fruit unsuitable for sale or consumption. Additionally, bat droppings can also damage fruit and create food safety concerns.
Image categorization methods may primarily be split up into two distinct categories: those that are based on machine learning (ML) and those that are based on deep learning (DL). In order to classify photos into the categories that are needed, ML-based image classification models depend on features that have been meticulously developed. Deep learning-based models use a huge picture dataset to the construction of deep convolutional neural networks (CNN).

II. Literature

In [9], the authors proposed that a new approach of real-time image processing known as the random bounce algorithm (RBA) be used for the vision-based detection of bats and birds. Extracting flight trajectories requires combining the RBA with object tracking in order to do this. The Bat trajectories are collected in a laboratory flight tunnel. The detection accuracy reported in the paper is 96.3%.
In their study, [10] the authors investigated five types of land cover - irrigated rice, hillside rice, secondary vegetation, forest fragments, and continuous forests. Over the period of November and December 2015, the researchers conducted acoustic research on insectivorous bats in and around Madagascar's Ranomafana National Park. The regional bat assemblage included 19 different species, which resulted in 9569 documented bat passes. Additionally, to identify harmful insect species consumed by bats, the authors collected feces from the six most commonly found bat species and performed DNA metabarcoding.
In the paper [11], the authors presented an algorithm that is suited for counting emerging bats in columns that have relatively consistent trajectories and velocities. This technique is based on statistical analysis. Column density is estimated at intervals of 1/30th of a second, and counts are gathered based upon column velocity. Individual bats are not recognised and tracked in this process; rather, counts are accumulated based upon the velocity of the column.
In [12], the authors examined the diets of two species of bats that are anticipated to offer pest management services across the maize belt of the United States: the large brown bat and the eastern red bat (Lasiurus borealis) (Eptesicus fuscus). In addition, the authors demonstrate that the selection of primers may have an effect on the variety of taxa found, and that recent developments in primer design can lead to improvements in diet detection investigations. They observed that both species of bats consume a wider variety of food than was previously reported by using novel ANML primers to extract prey DNA from faecal debris.
In [13], the authors highlighted the potential for insectivorous bats to act as natural samplers in order to identify (and maybe manage) pest species that are present in crops. Additional research is necessary to identify the entire scope of the rice water weevil's spread, and it is also necessary to examine integrated pest management strategies, including biological control, in order to reduce the populations of the rice water weevil.
In [14], the authors examined if bats eat insect problem species in macadamia plantations, with the added purpose of encouraging farmers to adopt a more integrated pest management strategy to pest control (IPM). The authors analysed bat pellets using fluorescently labelled and species-specific primers to get insight into the diet of insectivorous bats by using a molecular technique (COI). In the Levubu area of Limpopo, South Africa, between July 2015 and April 2017, faeces pellets were collected either from individuals that had been caught or from trays that had been set below roosts and bathouses. In order to produce species-specific primers and optimise the test, four of the most common

insect pests, including two species of moth (Lepidoptera: Tortricidae) and two species of stinkbug (Hemiptera: Pentatomidae), were collected.
In [15], the authors examined the top-down impacts of aerial insectivorous bats through suppressing insect populations by assessing damage to leaf and grape clusters. In addition, the authors investigated the benefits of these natural pest predators by quantifying the increases in potential vineyard yield that resulted from their presence. In grapevine plots that were protected from bats, the amount of leaf herbivory and grape cluster damage was much higher than in control plots. The total number of bat passes that we observed was 9872, out of which 9852, or 99.7%, were recognized and assigned to one of five species of flying insectivorous bats.
In [16], the authors evaluated how field edges stacked up against other landscape factors in terms of significance to bats. Bat activity in an intensively farmed terrain was evaluated using passive acoustic monitoring over 112 locations over the course of 17 consecutive summer nights. Every night, the authors collected data on bat species' night-time activity and community metrics (such as species richness and community habitat specialisation index) at a variety of distances from field edges and along a gradient of relative field margin density. In the 112 different research locations, we counted 11,445 bat passages. P. pipistrellus was the species that occurred in the greatest number of locations and accounted for 81% of the overall activity. It was found in 92% of the sites.
In [17], the authors developed a software tool called "Waveman" and produced a reference library utilising approximately 880 audio-files from 36 different species of Asian bats. In order to achieve the highest possible level of precision, the programme was designed using a brand new network known as "BatNet" as well as a re-checking method known as "ReChk." With an overall accuracy of over 90% and 0.94 AUC on the ROC plot, BatNet beats three other published networks in Waveman: CNNFULL, VggNet, and ResNet v2. When all 36 species are considered together, the categorization accuracy rates have a minimum of an 86% success rate.

III. Proposed Architecture

ResNet (short for Residual Network) is a deep neural network architecture that was introduced in 2015. The ResNet model is designed with the help of several residual blocks. These blocks are used in the network to overcome the vanishing gradient problem. The layers in which the wights are not updated over the iterations are bypassed with the help of the identity connection. The ResNet architecture is based on the idea of stacking residual blocks to create a very deep neural network. The original ResNet architecture has 152 layers, but there are also variants with fewer layers, such as ResNet-50 and ResNet-101. The number of convolutional layers that are included within each ResNet block is constant, while the number of filters that are contained inside each layer grows as the spatial resolution decreases. A global average pooling layer may be found at the very end of the network. This layer takes the activations from all of the feature maps and calculates an average across their whole spatial extent. After that, the output of the global average pooling layer is sent into a fully connected layer equipped with a softmax activation function. This results in the production of a probability distribution across the classes.

3.1 ResNet-50 Architecture

Since we have such a large number of pictures and classes, the conventional CNN method would not work for us because it demands a great deal of memory, time, and computer power. Because the dataset we picked produces a deep network, we have no choice but to make use of residual networks. The training of deep neural networks is sped up by the residual learning architecture, which ultimately leads to increased overall performance across all visual and non-visual tasks. These residual networks are far more in-depth in comparison to their "simple" counterparts; nonetheless, they still need the same number of parameters (weights). As can be seen in Figure 1, the residual link was included into the fundamental make-up of the residual network from the very beginning.

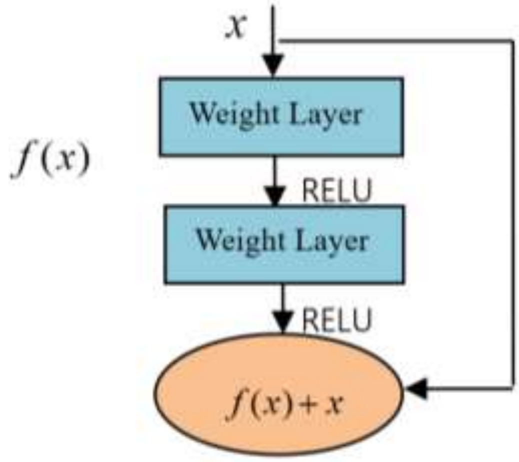


Figure 1: Basic Residual network Architecture.

3.2 Proposed modified ResNet-50 Architecture

The research approach that has been presented has a deep residual network with 50 layers. In order to develop the network, each layer incorporates both an identity block and a convolutional block into its design. In ResNets, the identity block serves as the default implementation of the standard block. This is the case when it is said that the dimensions of the input activation are similar. The proposed model is one of a kind since we have implemented a more sophisticated version that skips three hidden layers rather of two. This makes our model distinctive because it requires less time and produces accurate results.

An enhanced ResNet-50 network model is proposed here as part of this research. The residual link in residual blocks may be defined in Equation (1), in contrast to the earlier network models, which were as follows:

$$x_{l+1} = x_l + f(x_l, w_l) \tag{1}$$

Where x_{l+1} stands for the $(l+1)^{th}$ layer's residual block. x_l stands for the l^{th} layer's residual block. $f(x_l, w_l)$ indicates the portion of the block that is residual. In the event when the contours of the feature maps in x_{l+1} and x_l. The network requires the dimension operation since x_{l+1} and x_l are different. The following definition applies to the residual connection block:

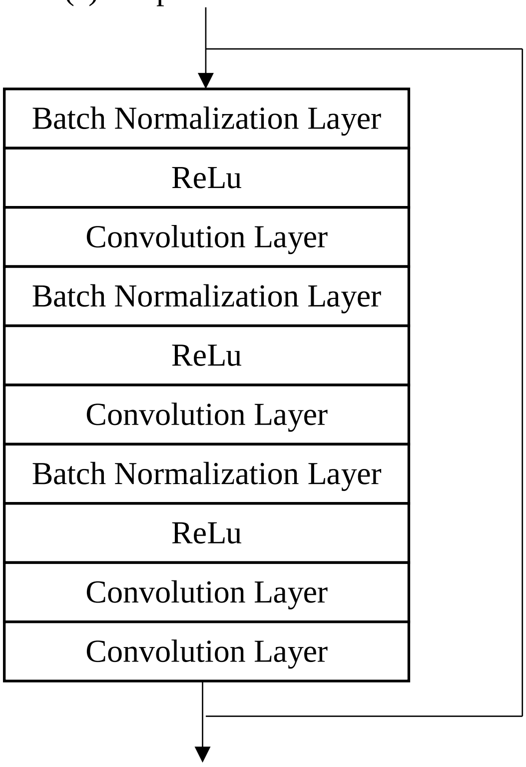
$$x_{l+1} = h(x_l) + f(x_l, w_l) \tag{2}$$

Here $h(x_l)$ is represented by 1X1 convolution operation. The residual connections in this research are separated into two block groups. To avoid gradient fading, the residual is linked between the input layer and the dense layer in the first block set. While the suggested technique creates a link between two block sets in the second block set, which is distinct from the original residual network. One layer's input is derived from the concatenated layer's output. Fig. 2 depicts the suggested model structure.

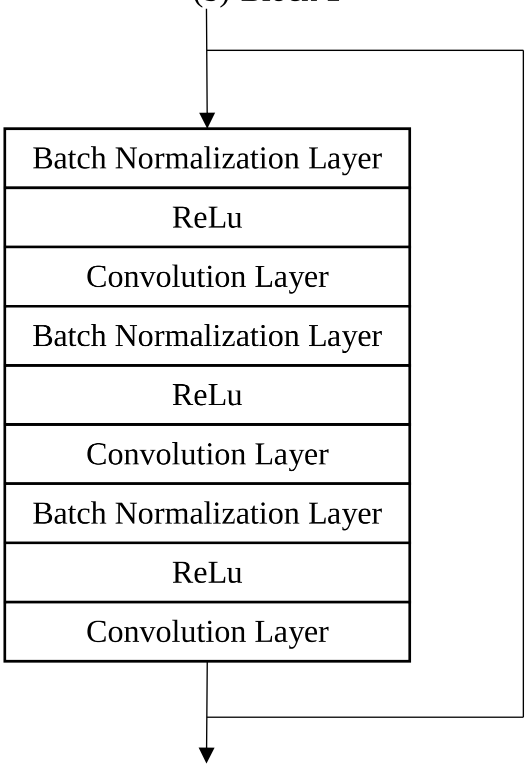
Input layer
Convolution layer
Max pooling layer
Block 1
Block 2
Block 3
Block 1
Block 2 X 2
Block 3
Block 1
Block 2 X 4
Block 3
Block 1
Block 2 X 2
Batch Normalization layer

ReLu layer
Max pooling layer
Dense layer
Dropout layer
Dense layer
Dropout layer
Dense layer

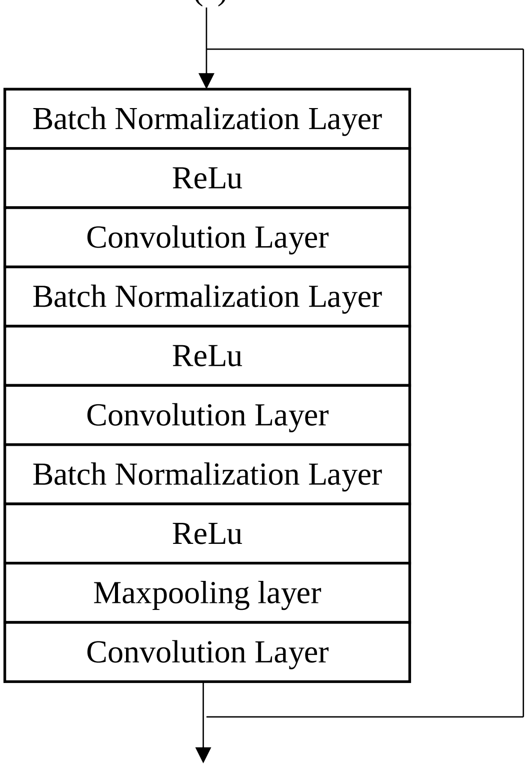
(a) Proposed ResNet model



(b) Block 1



(c) Block 2



(d) Block 3

Figure 2: Proposed ResNet50 Architecture

ResNet's design allows it to be deeper than previous architectures while maintaining or improving accuracy on benchmark tasks. This is because ResNet uses skip connections (also known as residual connections) that allow the network to learn residual functions, making it easier to optimize and reducing the risk of vanishing gradients. The skip connections enable the network to better generalize to new data, as it can learn to focus on the most important features of the input image and ignore noise or irrelevant details.

The convolution layer can learn to extract features from input images and identify patterns that are relevant to the task at hand, such as edges, textures, and shapes. This layer reduces the dimensionality of the input data while retaining the most relevant information. This can help prevent overfitting and improve the efficiency of the network. The convolution layer applies a non-linear function to the input data, enabling the network to model complex relationships between features and learn non-linear decision boundaries. The 2D convolution layer is the most frequent form of convolution that is used, and its abbreviation, conv2D, is used almost universally. The 2D input data are "slid" over by a filter or kernel in a conv2D layer, which then performs an elementwise multiplication on the data.

Maxpooling makes the network more robust to small translations in the input data by taking the maximum value within small regions of the feature maps, regardless of their location. This makes the network more invariant to small changes in the input, which can improve generalization. Maxpooling also reduces the spatial dimensions of the feature maps, which helps to reduce the computational cost of the network and prevent overfitting.

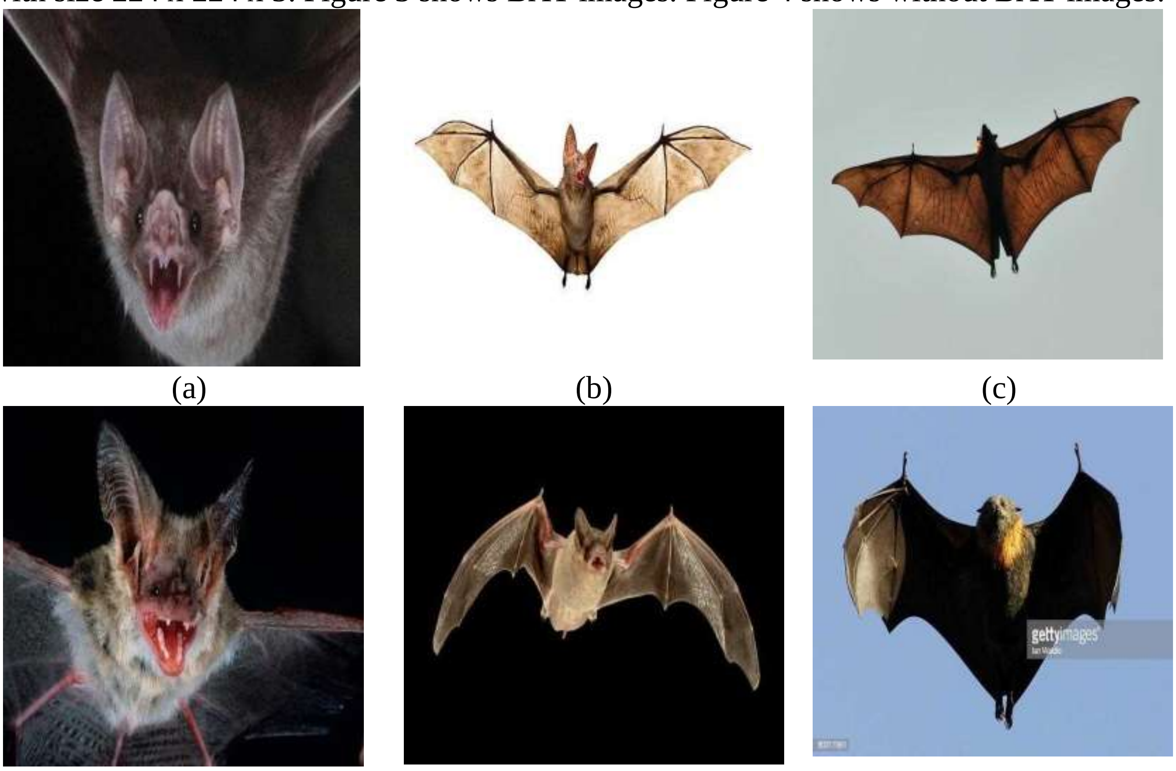
ReLU introduces non-linearity into the network, which enables it to learn more complex relationships between features in the input data. It can produce sparse feature maps by setting negative values to zero, which can help reduce overfitting and improve the efficiency of the network. Batch normalization helps to stabilize the distribution of activations across layers, making it easier to train deep neural networks. It also helps to prevent the vanishing gradient problem, which can occur when the gradients become too small to effectively update the weights of the network. Batch normalization acts as a form of regularization, which can help prevent overfitting and improve generalization.

Dense layers can be used to model complex non-linear relationships between inputs and outputs. They can also be combined with other types of layers, such as convolutional or recurrent layers, to create more complex architectures. Dense layers can learn to generalize from the training data and make accurate predictions on new, unseen data. This is particularly useful for tasks such as image or speech recognition, where the network must be able to recognize objects or sounds in a wide range of contexts.

IV. Results and Discussion

In this article, we report the results of Bats detections that were accomplished using modified ResNet50 deep learning model that we presented. There are a variety of datasets available for use in the bat detection process. The vast majority of the datasets are based on Western culture, but there is no systematic dataset that is based on our specific place in the world. There are a few species of bats that can be found in tropical Asia, however these bats are not included in the datasets established on the west.

The selected model is not ready to be fitted with the compiled dataset at this time. In order for any model to make use of the dataset in its entirety, it must first be cleaned up. For instance, the dataset contains photos of varying sizes, but in order for the images to be properly included into the deep learning model, they must all be kept at the same resolution. Our dataset contains photos from two hundred different classes, each of which is divided into one of two categories: BAT or without BAT. BAT has 600 images, while without BAT contains 600 images, all of which have associated labels with size 224 x 224 x 3. Figure 3 shows BAT images. Figure 4 shows without BAT images.



(a) (b) (c)

(d) (e) (f)

Figure 3: BAT Images

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(a)


(b)


(c)


(d)


(e)


(f)

Figure 4: Without BAT Images crop fields

When presented with a training dataset consisting of examples, the improved ResNet model is able to acquire the knowledge necessary to map inputs to outputs. An essential component of the process of training the network is locating a weighting scheme inside the network that has already been shown to be successful, or at the very least effective enough, in resolving the problem at hand. Figure 5 illustrates the validation loss that occurs throughout the training phase as well as the validation accuracy.

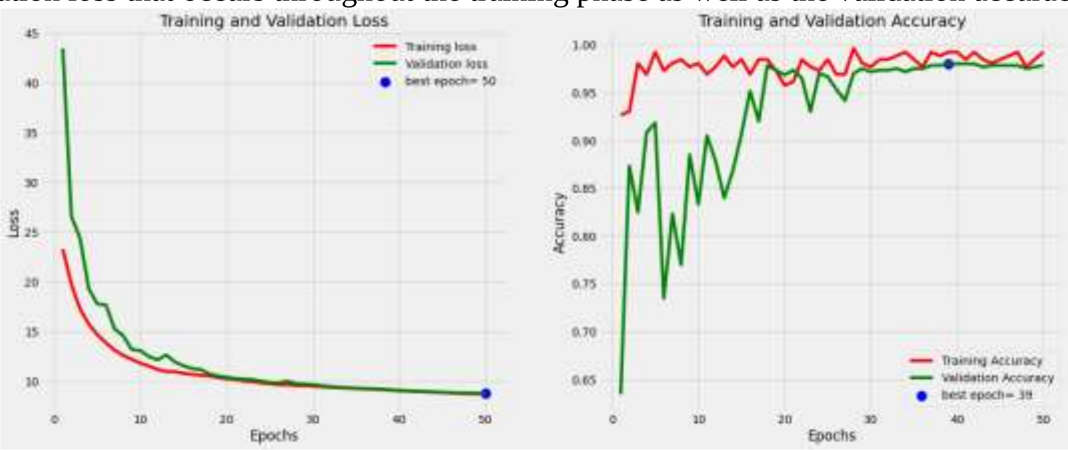

Figure 5: Validation Loss and Accuracy Plots of Proposed ResNet Model

To guarantee that each picture maintains the same proportions, it was scaled up to a resolution of 224 x 224 x 3. After subtracting the mean and obtaining the result by dividing it by the standard deviation, all of the images have been brought to the same level of accuracy via this technique.

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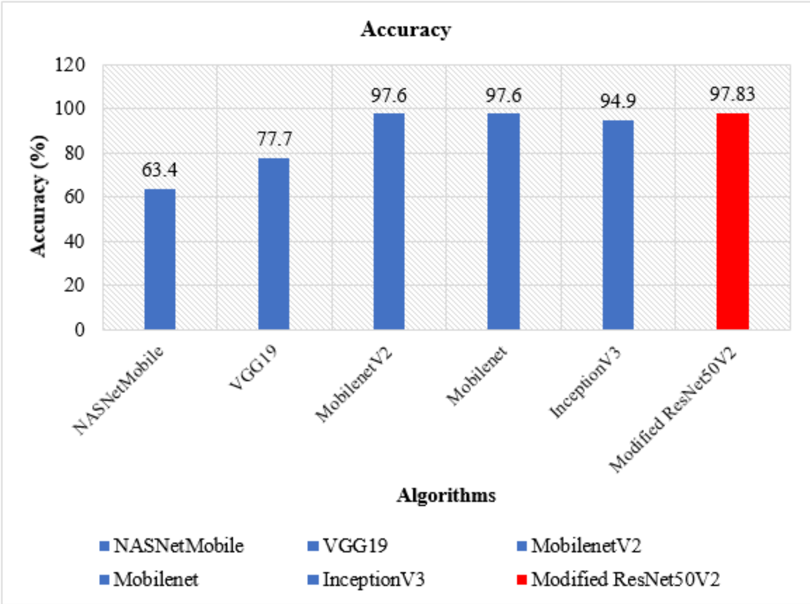

Figure 6: Comparative analysis

The comparative analysis is reported in figure 6. The proposed model was updated using the images. The dropout rate was set at 0.4, and the batch size was 32 in order to freeze certain neurons. As an optimizer, the stochastic gradient descent algorithm was utilised, and the learning rate was set to 0.001 while the momentum was set to 0.5. During the training phase of a deep learning model, the gradient values might potentially be quite high, which would result in an overflow issue. In contrast to the other approaches that have been used before, the newly presented model produced the highest quality output.

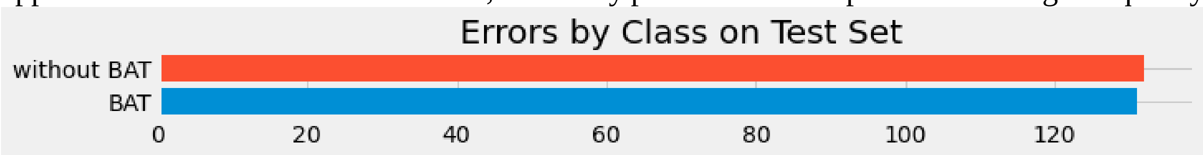

Figure 6: Errors by class on Test set for Proposed ResNet-50 model

The accuracy of the revised ResNet52 model that was suggested had been increased to the maximum level feasible, which was 97.83%. MobileNetV2 and MobileNet was successful in achieving an accuracy rate of 97.6%. NASNet came up with an accuracy score of 63.4% for its predictions. The accuracy that VGG19 was able to offer was 77.7%. It was possible for InceptionV3 to attain an accuracy of 95%. When compared to previous Network models, the findings demonstrated that the ResNet model that we presented attained a higher level of precision. The best version of our algorithm has shown an accuracy of 97.83% in predicting the presence of certain bat species in agricultural farmlands.

V. Conclusion

the growth of the human population and improved diets linked to higher standards of living will result in a doubling of food demand by 2050. To meet this demand, food production must increase by 70%. One strategy that may be taken to accomplish this objective is to reduce the amount of damage that is caused by bats. Bats are known to cause enormous economic losses to farmers as a result of their feeding habits, particularly in agricultural settings such as vineyards and orchards. They may be carriers of illnesses such as rabies and pseudorabies, both of which are contagious and may infect cattle and crops. This article demonstrates the use of computer vision and machine learning techniques to search for bats in photographs taken in agricultural regions. To record photographs of bats in agricultural settings, this technique commonly employs cameras that are outfitted with visible light sensors. The data that were collected as a consequence may offer information to farmers and other stakeholders about the activity of bats in their fields, such as the quantity of bats, the flight patterns that they engage in, and the times of the day when they are most active. Image categorization is handled via an altered version of the ResNet50V2 deep learning model inside the framework that was presented.

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