Detection and Classification of Dog Skin Disease using Deep Learning

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Abstract - Dogs are beloved pets and loyal companions to millions of people worldwide. Unfortunately, dogs can also suffer from a variety of skin diseases that can cause discomfort, pain, and even life-threatening complications. Some dog skin diseases can be transmitted to humans through direct contact. Early detection and treatment of these skin diseases are crucial for the health and well-being of dogs and humans. Our project aims to provide a quick and precise approach to identifying various types of skin diseases in dogs. To expedite the process of identifying and diagnosing infections related to canine interaction, we plan to utilize a machine-learning model. This approach aims to reduce the time and expertise required for accurate and consistent diagnosis, which can otherwise be challenging and time-consuming. Two models, InceptionV3 and MobileNetV2, were utilized and compared in our implementation. In the case of InceptionV3, a training accuracy of 0.99 and a validation accuracy of 0.98 were achieved. For MobileNetV2, we attained a validation accuracy of 96 and a categorical accuracy of 97.

Key Words: Dermatophytosis, zoonosis, image classification, deep learning, Transfer learning, InceptionV3, MobileNetV2, CNN, DNN.

1. INTRODUCTION

Dogs are prone to various skin diseases, which can cause discomfort and distress to them. A range of factors, such as allergies, infections, parasites, and autoimmune disorders, can lead to the development of these illnesses. While most of these conditions are not zoonotic, some of them can be transmitted to humans. Zoonotic skin diseases that can be contracted from dogs include ringworm, scabies, and impetigo. These diseases can cause skin rashes, itching, and blisters in humans, and they can be particularly harmful to individuals with weakened immune systems. It is therefore essential to take precautions when dealing with dogs that have skin diseases, such as wearing gloves and washing hands thoroughly after handling them. It is also crucial to seek veterinary care promptly to prevent the spread of zoonotic skin diseases and ensure the health and well-being of both dogs and humans. There are various causes of skin diseases in dogs, including allergies, infections, parasites, and autoimmune disorders. These conditions can be acquired from the environment, such as flea infestations, or they can be hereditary. Zoonotic skin diseases that can be contracted from dogs include ringworm, scabies, and impetigo. Dogs can catch these diseases through contact with infected animals, contaminated soil, or exposure to humans with these diseases. It is essential to practice good hygiene and seek veterinary care promptly if you suspect your dog has a skin disease to prevent the spread of zoonotic diseases and ensure the health and well-being of both dogs and humans.

Deep learning, specifically convolutional neural networks (CNNs), can aid in the early diagnosis of skin diseases in dogs. CNNs are a type of artificial neural network that can automatically learn and extract features from images. In the case of skin diseases in dogs, CNNs can analyze images of a dog's skin and identify any abnormalities, such as rashes or lesions, that could indicate the presence of a disease. This can be particularly helpful in the early detection of skin diseases, as visual symptoms may appear before other signs or symptoms of illness. By using CNNs, veterinarians and pet owners can quickly and accurately diagnose skin diseases in dogs, leading to prompt treatment and potentially preventing the spread of zoonotic diseases to humans.

Transfer learning is a deep learning technique that involves utilizing a pre-existing neural network model trained on a vast dataset, which has already acquired numerous features that are helpful for diverse tasks. With transfer learning, we can adapt the pre-trained model for a new task, such as classifying images of dog skin diseases, by refining its parameters. It refers to the approach of using the learning from one task on another task without the requirement of learning from scratch. To begin, you must train a model using a large data set. After that, you can fine-tune the model with a smaller data set more closely related to your particular issue. Although training on large data is always better as more patterns can be recognized, transfer learning can give satisfying results on small datasets. The transfer learning technique involves using an existing ConvNet feature extraction and the associated trained network weights, transferring to be fine-tuned on a small dataset. By using transfer learning, deep learning models can be trained with limited datasets. In transfer learning, information is transferred from a pre-trained model of a related domain and then fine-tuned on a small dataset.

2. RELATED WORK

Transfer learning is a deep learning technique that has been used to detect and classify dog skin diseases. Researchers have developed consensus models for each skin disease for dogs by combining the best models developed with normal and multispectral images using deep learning [1]. Deep convolutional neural networks (DCNN) have also been used to classify skin lesions into different categories, including dog skin diseases, with the help of their dermoscopic images [2]. Transfer learning has been employed to train segmentation models for two purposes: to extract the region of interest for classification and to classify high-frequency ultrasound skin images [3]. These studies demonstrate the potential of transfer learning in improving the accuracy of dog skin disease detection and classification.

In one study, transfer learning was used to train a public skin lesion dataset containing more than three skin diseases, and Inceptionv3 was one of the models used for classification [4]. This study performed a comparative analysis of six different transfer learning nets for multi-class skin cancer classification, and Inceptionv3 was found to be one of the best-performing models [2]. In this study, an image style transfer algorithm was applied to the detection of pigmented skin diseases for image augmentation, and Inceptionv3 was used for classification [5]. Overall, Inceptionv3 has shown promising results for skin disease classification and detection using transfer learning. One study proposed a computerized process of classifying skin disease through deep learning-based Long Short Term Memory [6]. [9] Compared MobileNetV1 and MobileNetV2, in which MobileNetV2 acquired higher accuracy. [10] Used Transfer learning in which they used DenseNet as a feature Extractor. [11] Proposed model based on improved MobileNetv2 for skin disease classification. [12] Proposed deep learning model using MobileNetV2 for classification of Sclerosis skin. [13] Implemented deep learning model using MobileNetV2 and compared with ResNet50V2, InceptionV3, in which the proposed system acquired the highest accuracy. [14] Trained a MobileNetV2 for skin cancer recognition. [15] Developed a deep learning model that outperformed other models like AlexNet, VGG16, and InceptionV3. [16] They employed models like ResNet50V2, VGG16, InceptionV3, and InceptionResNet for detecting skin disease and InceptionV3 resulted in the highest accuracy. [17] They used MobileNet and Xception for transfer learning for skin disease diagnosis, in which the Xception model resulted in higher accuracy. [18] They used several CNN models for transfer learning in which DenseNet resulted in higher accuracy.

[20] The study proposed two solutions to improve the performance of image classification in real-world tasks. The first solution was an input image denoising method, while the second solution was a dual-channel architecture that utilized an outline-enhanced image as an augmented feature. The dual-channel architecture achieved better accuracy than the original model, even in the presence of various types of quality distortion. [19] Experiments have shown that using certain image enhancement algorithms can have a negative impact on the performance of pre-trained CNN models when fine-tuning is used for transfer learning. Specifically, CLAHE, SMQT, wavelet transform, and Laplace operator all showed reduced performance on natural image datasets. Even adapt gamma correction showed lower mean accuracy, median accuracy, mean F1 score, and median F1 score compared to the original dataset.

3. METHODOLOGY

3.1 Dataset Gathering

In this study, we utilized a comprehensive dataset [21] of dog skin diseases consisting of four distinct types of conditions. These include healthy skin, bacterial dermatosis, fungal infection, and hypersensitive allergy. In total, our dataset contained a diverse range of 26 images depicting healthy skin, 12 images showcasing bacterial dermatosis, 11 images displaying fungal infection, and 13 images illustrating hypersensitive allergy. These images were carefully curated for use in both the training and the validation phases of our research.

We used the dataset images that were captured in the RGB color space. By utilizing this color model, we were able to analyze the color and intensity variations in the images, allowing for a more thorough understanding of the visual differences between the various skin diseases.

3.2 Data Preparation

In order to prepare the images for use in transfer learning models, we resized all images to a uniform size of (224,224). This standard size allowed for consistent input across all images and models used in our study.

As part of our data preparation process, we separated the labeled data into four distinct class folders, each corresponding to a specific type of skin condition in canines. These conditions included healthy skin, fungal infection, bacterial dermatosis, and hypersensitive allergic reactions. This separation of the labeled data into individual class folders allowed us to organize and categorize the data more effectively, enabling us to streamline the training and validation process for our machine learn machine-learning labeling and separating the data in this manner, we were able to ensure that each image was associated with the correct class, which was critical for achieving accurate results in our analysis. Throughout our study, we took great care to ensure that our data preparation process was rigorous and thorough. By separating the labeled data into individual class folders, we were able to create a more structured and organized dataset, which facilitated the development of our models and enabled us to diagnose canine skin conditions more.

For this purpose, we utilized all available labeled data for both the training and the validation of our models. The labeled data were randomly split into two folders with a ratio of 8:2, ensuring that both training and validation sets were representative of the entire dataset. To ensure that important features were visible for feature extraction, we applied image enhancement techniques to all images in both the training and validation sets. Specifically, we increased the brightness of each image by a factor of 2, allowing for clearer visualization of important details. To increase the size and diversity of our dataset, we employed data augmentation techniques such as zooming, horizontal flipping, and vertical flipping. This process resulted in a larger and more diverse dataset, which improved the robustness and generalizability of our models.

In total, our training dataset contained 443 images, while our validation dataset contained 114 images. The use of various preprocessing and augmentation techniques helped to ensure that our models were trained and validated on a high-quality and representative dataset, which is crucial for achieving accurate and reliable results in our study.

3.3 Feature Extraction

In classification problems, one of the most crucial process is feature extraction. To achieve this we have used pre-trained transfer learning models. We implemented model training using two CNN architectures MobileNetV2 and InceptionV3 using TensorFlow and Keras. Feature extraction involves identifying significant features within an image and deriving information from them. This is accomplished by stacking multiple CNNs in sequence to form a comprehensive model.

3.4 Model Implementation using MobilNetV2

MobileNetV2 is a lightweight deep-learning model designed specifically for mobile devices. Its architecture consists of depth-wise separable convolutions that reduce the number of parameters and computations required while maintaining high accuracy. During feature extraction using MobileNetV2, the pre-trained model is loaded and the final classification layers are removed. This allows us to use the model as a feature extractor, where the output of the last convolutional layer is used as a set of image features. These features are then fed into a new classifier, which is trained to recognize the target classes of the specific task at hand. [7] MobileNetV2 has two main building blocks: the inverted residual block and the linear bottleneck block. The inverted residual block consists of a 1x1 convolution that increases the number of channels followed by a depth-wise separable convolution and another 1x1 convolution that reduces the number of channels. This block is designed to increase the non-linearity of the network while keeping the number of parameters low. The linear bottleneck block consists of a 1x1 convolution that reduces the number of channels followed by a depth-wise separable convolution and another 1x1 convolution that increases the number of channels. This block is designed to increase the representational power of the network while keeping the computation low. MobileNetV2 has achieved state-of-the-art performance on several benchmarks and has many applications for mobile devices. MobileNetV2 is a significant advancement in deep learning and has opened up new possibilities for mobile applications.

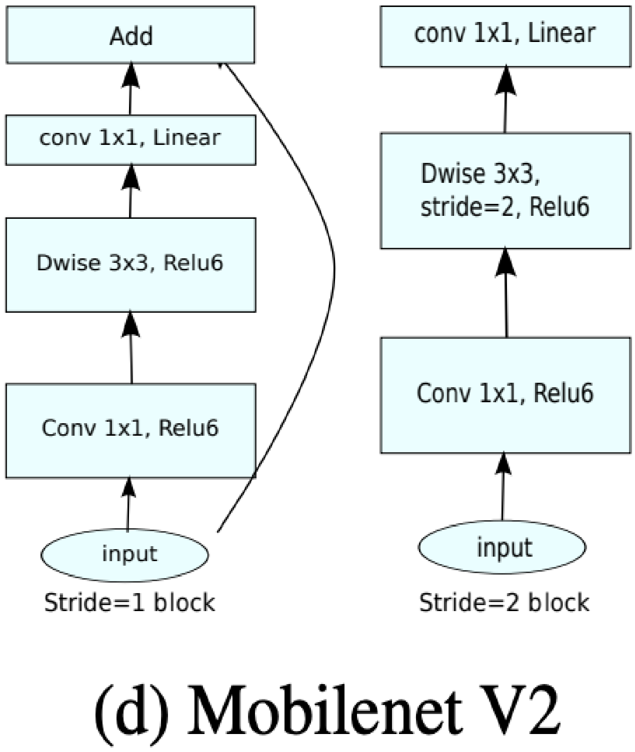

Figure 1. Architecture of MobileNetV2 [7]

Our study involved the implementation of MobilNetV2, a deep learning model that is optimized for mobile devices, and training the model using a dataset of images with dimensions of (224, 224, 3). The output of the trained model is an array of four elements, which represents the probability of each of the four classes which are healthy skin, fungal infection, bacterial dermatosis, and hypersensitive allergic reactions. To mitigate the risk of overfitting, a dropout layer was added to the model architecture. Additionally, categorical cross entropy was utilized as the loss function during the training phase. The model was trained for a total of 31 epochs. Upon completion, the model attained a validation accuracy of 94% and training accuracy of 97%, indicating that it performed exceptionally well on the validation set. The below graph (Figure 2) represents the trend of training accuracy vs validation accuracy of our MobileNetv2 model.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

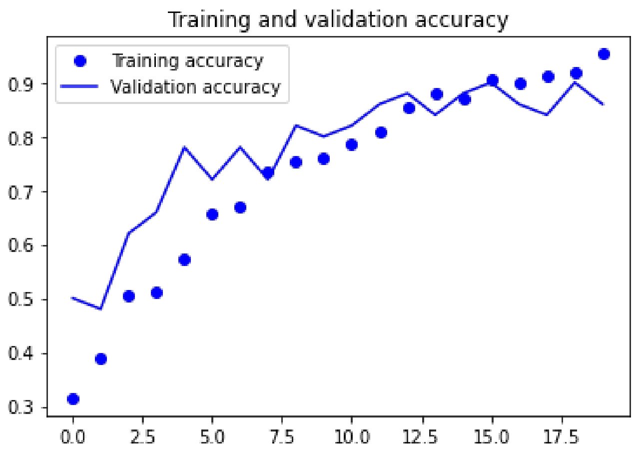

Figure 2. Training and validation accuracy graph

The graph (Figure 3) presented below depicts the trend of the training loss vs validation loss of our MobileNetv2 model.

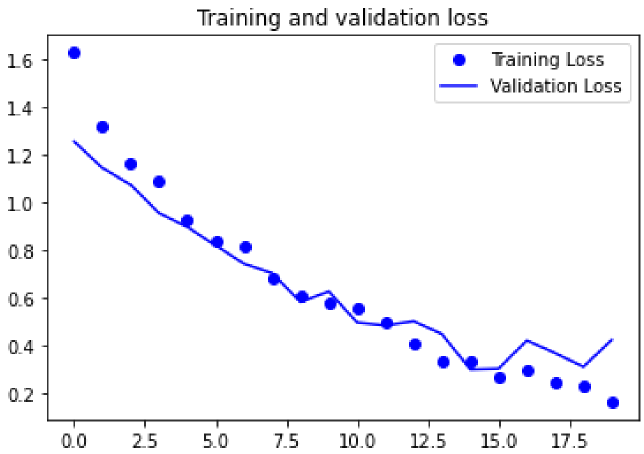

Figure 3. Training and validation loss graph

3.5 Model Implementation using InceptionV3

Inceptionv2 features several design improvements over the original architecture, resulting in superior performance on a variety of image classification benchmarks. The Inceptionv2 architecture is characterized by its use of "Inception modules," which are essentially multi-path convolutional neural networks. This module is designed to compute convolutions at multiple levels of abstraction, specifically 1 × 1, 3 × 3, and 5 × 5 convolutions, all within the same module of the network. These different convolutional filters allow the network to capture features at various levels of detail and abstraction, enabling it to better recognize patterns within images. These modules perform convolutional operations at multiple scales and concatenate their outputs, these outputs are then fed into the next layer of the network. This approach results in more efficient use of computational resources and enables the network to better capture both low-level and high-level features in images. One key innovation of the Inceptionv2 architecture is its use of "factorized" convolutional filters, which reduce the computational cost of convolutional operations by breaking them down into smaller operations. This allows the network to perform more complex computations while still maintaining a manageable number of parameters. Another important design feature of Inceptionv2 is its use of "batch normalization," which involves normalizing the input to each layer of the network to reduce the effects of internal covariate shift. This technique results in faster training times and improves the overall performance of the network. Inceptionv2 also utilizes other optimization techniques such as "label smoothing" and "weight decay" to further enhance its performance on image classification tasks. Overall, the Inceptionv2 architecture stands out from other neural network architectures due to its effective use of multi-path convolutional networks, factorized convolutional filters, and other optimization techniques. These design improvements result in a network that is both efficient and effective at image classification. The inception V3 model consists of a total of 42 layers, which represents a slight increase in layer count compared to the previous inception V1 and V2 models. However, despite this increase in complexity, the inception V3 model exhibits an impressive level of efficiency.

We developed a deep learning model using the InceptionV3 architecture, implemented using the TensorFlow and Keras libraries. As the available dataset was limited, a dropout layer was added to the model to prevent overfitting, which is a common problem in deep learning models. Additionally, the categorical cross-entropy was selected as the loss function for the model, which is a widely used measure for

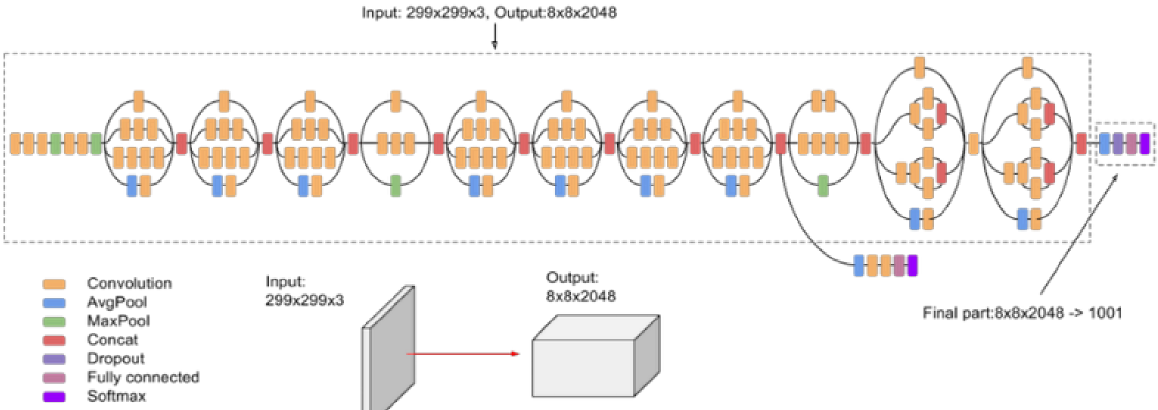

Figure 4. Architecture of InceptionV3 [8]

evaluating classification models. To further optimize the performance of the model, an early stopping and checkpoint mechanism was employed, where the validation accuracy of the model was monitored during the training process. The weights associated with the best validation accuracy were saved at each epoch, thereby allowing the model to be fine-tuned at any point during the training process.

The performance of the model was evaluated by plotting and analyzing the trend of both training accuracy and validation accuracy over each epoch. This graphical representation (Figure 5) provided a clear and concise summary of the model's performance over time, with the addition of a dropout layer and the use of categorical cross entropy as the loss function, resulting in a model with impressive validation accuracy of 98% and a training accuracy of 99%.

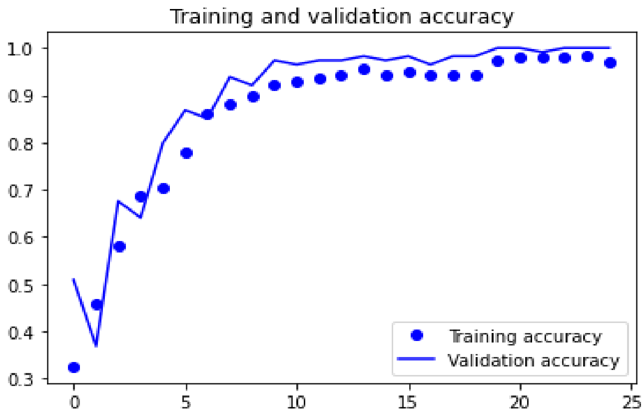

Figure 5. Training accuracy and validation accuracy of the model using InceptionV3

The below graph (Figure 6) is the representation of the trend in training loss and validation loss with epochs.

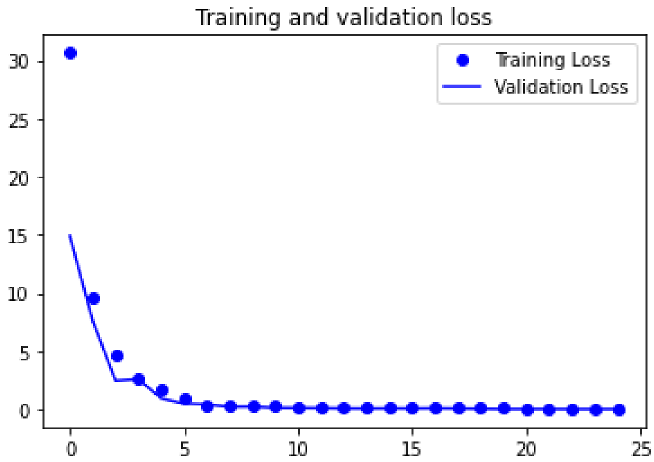

Figure 6. Graph of training and validation loss of our model using InceptionV3

4. RESULTS

This section presents the results and analysis of two models developed for the classification of bacterial dermatosis, fungal infection, healthy, and hypersensitive allergy. The first model was developed using the InceptionV3 architecture, while the second model was developed using MobileNetV2. The below table (Table 1) represents the Classification report and (Figure 7) represents the confusion matrix of the InceptionV3 model.

Table 1. Classification report of InceptionV3 model.

	Precision	**recall**	**F1-score**
Bacterial	1	1	1
Fungal	1	1	1
healthy	1	0.97	0.98
hypersensitivity	0.97	1	0.98

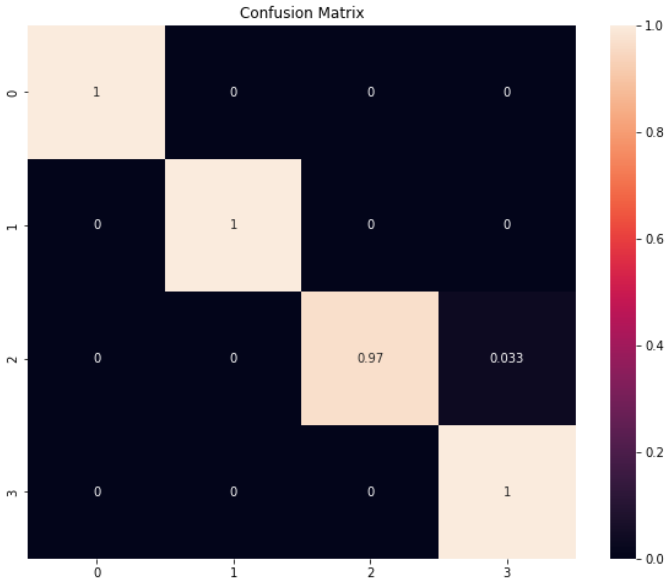

Figure 7. Confusion matrix of InceptionV3 model.

The performance of the two models was evaluated using the F1-score metric, which is a measure of the harmonic mean of precision and recall. The F1-scores of the InceptionV3 model for bacterial dermatosis, fungal infection, healthy, and hypersensitive allergy were 1, 1, 0.98, and 0.98, respectively. On the other hand, the F1-scores of the MobileNetV2 model for bacterial dermatosis, fungal infection, healthy, and hypersensitive allergy were 0.96, 1, 0.93, and 0.97, respectively. The below table (Table 2) represents the classification report and (Figure 8) shows the confusion matrix of the MobileNetV2 model.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

Table 2. Classification report of MobileNetV2 model

	Precision	recall	F1-score
bacterial	1	0.93	0.96
Fungal	1	1	1
Healthy	0.93	0.93	0.93
hypersensitivity	0.94	1	0.97

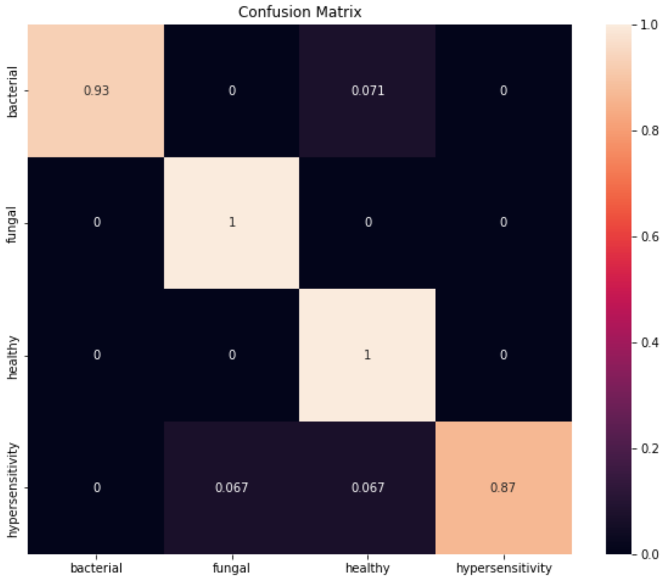

Figure 8. Confusion Matrix of MobileNetV2 model

Moreover, the InceptionV3 model showed a validation accuracy of 98% and a training accuracy of 99%, which is higher than the MobileNetV2 model's validation accuracy of 94% and training accuracy of 97%. The results suggest that the InceptionV3 model outperforms the MobileNetV2 model in terms of accuracy.

In conclusion, the findings demonstrate that the InceptionV3 architecture is more effective in classifying bacterial dermatosis, fungal infection, healthy, and hypersensitive allergy, with superior performance in both F1-score and accuracy.

5. CONCLUSION

The early detection of dog skin diseases is crucial to prevent their transmission to humans. With this objective in mind, we trained deep learning models using InceptionV2 and MobileNetV2. Our results showed that InceptionV3 achieved the best validation accuracy of 98% in detecting various types of skin diseases in dogs, while MobileNetV3 attained a validation accuracy of 94%. Furthermore, we utilized data enhancement and data augmentation techniques to improve the performance of our models. This approach enables us to identify and treat dog skin diseases at an early stage, ultimately promoting the health and well-being of both dogs and humans. In summary, our research highlights the significance of early detection and demonstrates the potential benefits of machine learning in veterinary medicine.

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