Classification of Canine Skin Disease using Deep Learning Algorithms

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Abstract - Dogs were the most common pet in India in January 2022, with a share of 68 percent, a share of 34 percent cats are the second-most popular pet, according to a Rakuten Insight poll on pet ownership. Canine interaction has been identified as a risk factor for several zoonotic illnesses caused by bacteria, fungi, parasites, and viruses through direct or indirect contact. Additionally, the doctor needs to have a list of infection diagnoses and routinely inquire about the existence of dogs in the home and their health. We intend to deploy a machine learning model to decrease the time and effort necessary for establishing a consistent infection because these procedures take time and a high level of skill set. We studied and compared various approaches researchers have used in similar situations.

Key Words: Dermatophytosis, zoonoses, image classification, deep learning, MobileNet, CNN, KNN, LSTM, MLP.

1.INTRODUCTION *(Size 11, Times New roman)*

Over 70 human diseases have links to infections in dogs. Given that a dog's health diagnosis requires a veterinarian's skill, an artificial intelligence model for spotting dog ailments might greatly cut down the time and expense needed for a diagnosis and effectively maintain animal health. Even though owning a dog can have positive effects on one's mental and emotional health, dogs can occasionally contract various illnesses and infections. Dogs' skin conditions can be brought on by several factors, or possibly a combination of them. A zoonotic illness is an infection or disease that can spread naturally from vertebrate animals to humans or from people to vertebrate animals. More than 60% of infections that affect humans are zoonotic. They comprise numerous pathogens, such as bacteria, viruses, fungi, protozoa, parasites, and others. Zoonoses have been significantly impacted by variables like climate change, urbanization, animal movement and trade, travel and tourism, vector biology, anthropogenic influences, and natural elements.

More zoonotic illnesses are developing and redeveloping over time. The most prevalent zoonotic dermatoses in dogs and cats include dermatophytosis, fleas, cheyletiellosis, and scabies. Fleas, ticks, mites (mange), biting flies, mosquitoes, and young parasitic worms are parasites that can lead to a variety of skin conditions. Skin cancer, pyoderma, seborrhea, allergy, demodectic acariasis (demodicosis), sarcoptic acariasis, immune-mediated skin disease, endocrine-related skin disease, and acral lick dermatitis were the top 10 diagnoses. For very young children, expecting mothers, the elderly, and immunocompromised individuals, these infections can be bothersome and even life-threatening. Dermatophytosis, or "dermatophytosis" (from the Greek "dermos" meaning "skin"), is a zoonotic disease that is frequently linked to dogs and is brought on by a range of skin fungi that can infect both humans and animals. Microsporum, Trichophyton, and Epidermophyton are three genera of fungi that are responsible for the infection known as dermatophytosis. Hair loss, scaling, and crusting are indications or symptoms of Dermatophytosis. Usually, it causes a circular, red, itchy, and scaly rash. Infections with ringworm, tinea corporis, tinea capitis, and other dermatophytoses are caused by the fungus Microsporum (fungal infections of the skin). Tinea pedis, especially the vesicular kind, tinea corporis, and occasionally superficial nail plate invasion in people are all frequently brought on by the anthropophilic fungus Trichophyton interdigitale. E. floccosum is one of the shallow and cutaneous mycoses caused by the genus Epidermophyton, as well as tinea corporis (ringworm), tinea cruris (jock itch), tinea pedis (athlete's foot), and tinea unguium (fungal infection of the nail bed).

Skin diseases can be determined by visiting vets, but detection can take time. These skin diseases, if detected at an early stage can reduce the spread of disease and can prevent a lot of trouble for dogs and dog owners. The goal of this study is to develop an application that can be used to detect the type of disease, and other medication findings related to diseases. In addition, it will also help to determine the precautions that need to be taken. This application should be optimized for mobile devices. Using computer vision, image processing, and deep learning algorithms, this can be achieved. There are many studies available detecting human skin disease, we will be analyzing these, to find the most accurate, effective, and optimal way to detect canine skin diseases.

Image processing helps by extracting features that play a role in determining the type of skin disease. By utilizing deep learning algorithms, the model can be trained for specific types of diseases using existing images from the dataset.

2. LITERATURE SURVEY

According to [1] a deep learning algorithm that uses inception-v4 as a basis considered all major causes of skin diseases, 45 metadata variables related to patient and medical history, and about 1 to 6 images of skin conditions were concatenated, and the output of image processing and metadata were evaluated. They generated color gradients and used K-means clustering to detect the spread of diseases and used feedforward backpropagation ANN for classifying the diseases in [2]. Using a convolutional neural network, [4] has proposed a method for extracting essential features from colored skin images and identifying disease. They preprocessed images in sequence for producing 6 results from the original image. The six filters were a grey image, sharpening image, median image, smooth filter image, and binary mask. YCbCr was used to extract color codes from diseased skin. Used feed-forward ANN for training and testing purposes. [3] extracted features from color images and classified them using a multiclass SVM. [5] proposed a system based on deep learning that uses MobileNet V2 and Long Short Term Memory (LSTM), with one based on MobileNet V2 showing higher efficiency and accuracy for small computation devices. An automated colposcopy image analysis framework is presented in [18] for the classification of precancerous and cancerous lesions of the uterine cervix. It is based on MobileNetV2 networks. As a solution to the problem of Colposcopy image classification, MobileNetV2 is used, as it provides optimized memory consumption and high performance at a low cost. [26] In this study, they developed a model for studying the changes in gray matter (GM) tissue in the spinal cord. Their deep image segmentation model was developed using UNet architecture and a pre-trained MobileNet-V3 model, which they named MobileNet-V3-UNet. The UNet model can accept images of all sizes. MobileNetV3 is more efficient for mobile devices as it reduces the number of parameters and achieves higher classification accuracy. [27] Using the images generated by MRI brain tumors, they devised a model for detecting the type of brain tumor. The researchers used the MobileNet V2 140 x 224 model, one of the convolutional neural network architectures, and achieved 94% accuracy. As MobileNet V2 140 x 224 overcomes the need for excess computing resources by dividing convolution into depthwise convolution and pointwise convolution.

[6] The proposed network for diagnosis of skin abnormalities using CNN, and MLP, focused on simplification of network structure for use on a mobile device or a portable lightweight medical device. Color channels that were most effective and informative for the network were extracted using a pruning algorithm that led to the simplification of the network. The proposed MLP structure performed best with low computational power. [16] used CNN-based Resnet-152 to classify clinical images of 12 skin diseases. [8] Proposed a feature block for extracting boundary details and channel-wise dimensions. This improved the extraction of accurate boundaries and spatial information. [10] In this study, a classification model was developed based on a lightweight CNN, MobileNet. Modified MobileNet showed better performance, F1- score, than traditional MobileNet. The proposed model consisted of 13 layers of depthwise convolution layers. Batch normalization and ReLU activation function after each depthwise and pointwise convolution layer. All of these layers were used for feature extraction and a pooling layer was used to reduce the size of the extracted feature maps. We replaced the last five layers of classical MobileNet with a dropout layer and fully connected layer and used the softmax activation function. In [11], FCRN (Fully Convolutional Residual Networks) and CNN were used for classification, and contrast enhancement and FCRN were used for segmentation in the proposed system. Using data augmentation, enhancement, and segmentation, [12] first examined images and extracted features such as color, shape, and texture. Used deep learning algorithms CNN and LSTM for the classification of psoriasis types. CNN showed an accuracy of 84.2% and LSTM showed an accuracy of 72.3%. [14] They used feed-forward neural networks to classify images in this study. [16] used CNN-based Resnet-152 to classify clinical images of 12 skin diseases. [17] have proposed a residual network to simplify the training of networks.

The residual network showed an error rate of 3.7% on the ImageNet test set. Three types of diseases are recognized in this [19] study, which includes herpes, dermatitis, and psoriasis. They used a grey-level co-occurrence matrix (GLCM) for segmentation. The analysis of vertical image segmentation is used to identify and recognize the different types of skin diseases. They applied a Support vector machine (SVM) for the classification of different diseases. In this study, irrelevant variables are reduced by applying image filtering, image rotation, and Euclidean distance transformation applied to image preprocessing. In [13], we used pixel values of five different color spaces of disease and applied a group of machine learning classifiers to classify different types of diseases. We used KNN, DT, NB, SVM, MLP, and RF for classification, and we compared their performance. They proved that the results of feature vectors based on pixel values in five color spaces showed higher performance with an accuracy of 97.4% for psoriasis. [20] In this study, based on the K-NN classifier nearest neighbor (K-NN), an algorithm for the classification of non-melanoma skin lesions was applied. Hierarchical classifiers are used in this study because they are highly efficient and flexible in expressing the discriminant power of various types of features. A hierarchical classification framework was used to select the most relevant features.

Framework showed an accuracy of more than 93% in the classification of two major classes and an accuracy of 74% overall in five classes. [21] Researchers used GLCM (Grey Level Co-Occurrence Matrix) features, and wavelet decomposition for normalization with a K-NN classifier in this study to classify human skin diseases such as acne and psoriasis. It has 100% accuracy for acne and 92% accuracy for Psoriasis. [22] This study proposes a model for skin lesion detection of diseases. Gaussian smoothing was used to overcome noise and hair in the available dataset of images. A region-growing method was applied for segmentation. The classification was done with SVM, KNN, and a combination of SVM and KNN classifiers. The combination of KNN and SVM classifiers resulted in an F-measure of 61%, which was better than each of the individual KNN and SVM. [24] have presented a combination of computer vision and machine learning to identify dermatological diseases. First, the image of the skin disease is preprocessed for feature extraction, for which they used ANN and the maximum entropy model. Training and testing were conducted using decision trees and KNN algorithms. [23] ANNs have been demonstrated to be an effective classifier in mammography for the classification of masses and microcalcifications. In the field of ANN mammography, the implementation of a three-layer perceptron-based neural network using backpropagation algorithms has become a significant advancement. [9] This study used RGB component analysis and texture information for texture analysis. GLCM, key points, and color channel information were applied for the classification of images. The classifier and variance used in the study include the Stochastic Gradient Classifier, Naïve Bayes Classifier, Decision Tree Classifier, Random Forest Classifier, KNN Classifier, Support Vector Machine Classifier, and Model Logistic Regression Classifier. [15] used both texture features and skin color for the recognition of skin disease study. This study proposed human skin detection using pixel-level detection. The RGB approach was not accurate, according to the study. Hence, RGB Ratio can be increased by adding ratios of R/B and G/B. This approach had shown better results. [7] Using image-based supervised learning and multiscale superpixel-based cellular automata, probability maps for different skin areas are calculated using a superpixel method for dermoscopy images. The proposed system showed more accuracy and was more reliable than state-of-the-art methods. As per [25], there are two methods. First, there is local optimization on mobile devices, and second, there is distributed optimization. Local optimization can be achieved by either improving the algorithms or by reducing the size of the neural network. Another way is to use the cloud for distributed deployment framework.

3. DISCUSSION

A lot of CNN algorithms can be used for mobile vision applications. CNN algorithms are the main techniques that are used in mobile applications for classification tasks. They show better time and space complexities as compared to others. MLPs indeed have simpler structures than CNNs, but CNN's tend to perform better than MLPs. As long as we can maintain the performance and accuracy of the CNN structure, then it can be simplified. The most appropriate option that could give high performance would be MobileNetV2, which is suited to large and diverse data sets. In [24], however, the authors used K Nearest Neighbour in their application. KNN and SVM can be applied as classifiers as well. LSTMs are also a type of neural network i.e recurrent neural networks were also applied by the researchers for image classification. The authors of [5] used MobileNet-V2, the authors of [18] used MobileNet-V2, the authors of [26] used MobileNet-V3, and the authors of [27] used MobileNet V2 140 x 224. Throughout the articles, CNN-based MobileNet algorithms are applied to all the various scenarios, resulting in higher accuracy, a lower computational cost, and efficient performance. Binary images and GLCM (grey-level co-occurrence matrix) could both be used to preprocess photos. To extract feature information, contrast enhancement may be applied. Another method for boosting data to produce a dataset of higher quality is data augmentation.

4. CONCLUSION

The major objective of this study was to anticipate the detection of the zoonotic disease Dermatophytosis. It was to give consumers the necessary remedies more quickly. This was done by utilizing computer vision, and deep learning models and evaluating their performance on various metrics. We compared the performance outcomes of machine learning techniques on a variety of performance metrics to detect dermatophytosis in canines. Furthermore, a deep learning system had to be suitable for mobile devices to be used in the form of an application. The primary methods for classification problems in mobile applications are CNN algorithms. When compared to others, they exhibit greater time and spatial complexity. As mentioned in the discussion section, CNN can be changed or rebuilt to classify skin conditions in canines. Additionally, other algorithms like LSTMs, MLPs, and SVM could be employed.

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