COWS LUMPY VIRUS DETECTION USING DEEP LEARNING

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ABSTRACT

Animal illness is now a widespread problem. sickness identification is essential because there are various sorts of sickness in creatures, and the opinion will be delivered in a timely manner. Cows with the Neethling infection develop lumpy skin complaints. The affection of these illnesses causes lasting harm to the cattle's skin. Reduced milk production, gravidity, poor growth, revocation, and, in severe cases, mortality, are the most common effects of the illness. We developed a deep learning-based architecture that can predict or detect disease. To discover the pathogen that causes lumpy skin problem, it is crucial to employ a deep literacy system. DenseNet- 121 is an efficient system for reading prints that is based on deep literacy.

This study shows that convolutional neural networks are capable of predicting LSDV in animals using photos and images alone. Images were divided into the LSDV and Non-LSDV classes using the specified deep learning model. Because there is currently no LSDV vaccination that can treat rather than control the virus, early and accurate viral identification can be an implicit mechanism for identifying and stopping the spread of the infection.(For instance, by dividing the Animals).

Keywords: Beast Lumpy Skin Complaint, Deep Literacy, Convolutional Neural Network, Densenet- 121, Image Processing, Transfer Learning.

1. INTRODUCTION

The virus (LSDV) that causes lumpy skin disease can infect cattle. Ticks and other animals that feed on blood, such as flies, mosquitoes, and ticks, spread it. Animals who have never been exposed to the disease may develop nodes on their skin, a fever, and even pass away as a result of it. Two methods of control are vaccinations and rewarding afflicted creatures. The purpose of this study was to evaluate how well some deep learning algorithms could understand the context of an infection causing a Lumpy Skin complaint. For the purpose of diagnosing lumpy skin illnesses, transfer learning methods based on CNN have been donated on numerous occasions. Medical image datasets include fewer training examples than other types of image datasets. Attacking the issue of fading gradients, enhancing feature reuse, and minimising parameter consumption are the key goals of employing densenet-121, all of which are lucrative while training deep learning mode.

2.EXISTING SYSTEM

In existing systems evaluating multilayer perceptron and artificial neural networks (ML) (SVM, decision tree, adaBoost, bagging). ways in sooth saying LSDV actuality based on meteorological and geospatial. And Application of AI in image processing for cattle disease opinion. Using the tensor flow architecture, conventional preprocessing techniques were used for CNN mining, and a web-based approach was used for classification.. Disadvantage • However, the existing models take issue with complexity, cost, mortal-reliance, and inaccuracy. • likewise, the limitation of datasets is another practical problem in this arena of exploration. In addition, every deep literacy model demands a metric to judge its performance

3. PROPOSED SYSTEM

We developed a machine learning armature that can prognosticate or descry illness. To discover the pathogen

that causes lumpy skin problem, it is crucial to employ a deep learning system. DenseNet-121 of transfer learning is a deep learning-based system that successfully recognizes photos. This study shows that convolutional neural networks can accurately measure LSDV in animals using visuals from the filmland. The classification of photos into the groups LSDV and Non-LSDV (Normal Skin) employed the hand-crafted deep learning model.

4. IMPLEMENTATION

Data collection:

Obtain a dataset of animal images with lumpy skin disease, categorized as normal, diseased. The dataset should be diverse and representative of different animal skins. It's important to ensure that the dataset is labeled correctly and contains a sufficient number of samples for each category.

Data pre-processing:

Resize the images to a uniform size, such as 256x256 pixels, to ensure consistency. This step is important because the input images must have the same dimensions for the model to process them effectively. Normalize the pixel values to a range between 0 and 1 by dividing them by 255. This normalization step helps in better convergence during model training.

Data augmentation:

To increase the diversity and variability of the dataset, generate new images from the existing dataset through data augmentation techniques. This can include random rotations, zooming, horizontal or vertical flipping, and shifting. Data augmentation helps in improving the model's ability to generalize to unseen data and reduces overfitting.

Model selection:

Choose DenseNet121 as the pre-trained model for image classification. DenseNet121 is a deep convolutional neural network architecture that has shown excellent performance on various image classification tasks. It has a large number of layers and a high capacity to learn complex features from images.

Transfer learning:

Utilize transfer learning by leveraging the pre-trained DenseNet121 model as a feature extractor. Freeze the weights of the initial layers of the model and only fine-tune the later layers to adapt it to the lumpy skin disease dataset. This approach saves computational resources and training time while still benefiting from the knowledge learned by the model on a large dataset.

Model evaluation:

Evaluate the performance of the trained model using appropriate metrics such as accuracy, precision, recall, and F1 score. Split the dataset into training and testing sets to assess the model's ability to generalize to unseen data. Additionally, consider using techniques like Adam optimizer for a more robust optimization.

Model deployment:

Save the trained model along with its learned weights and architecture for future use. This allows the model to be deployed and utilized for inference tasks without the need for retraining.

Inference:

Using the trained model, classify new animal images with lumpy skin disease as normal and Diseased. Pre-process the input image by resizing it to the required input size and normalizing the pixel values. Pass the preprocessed image through the trained model and obtain the predicted category or probabilities for each category.

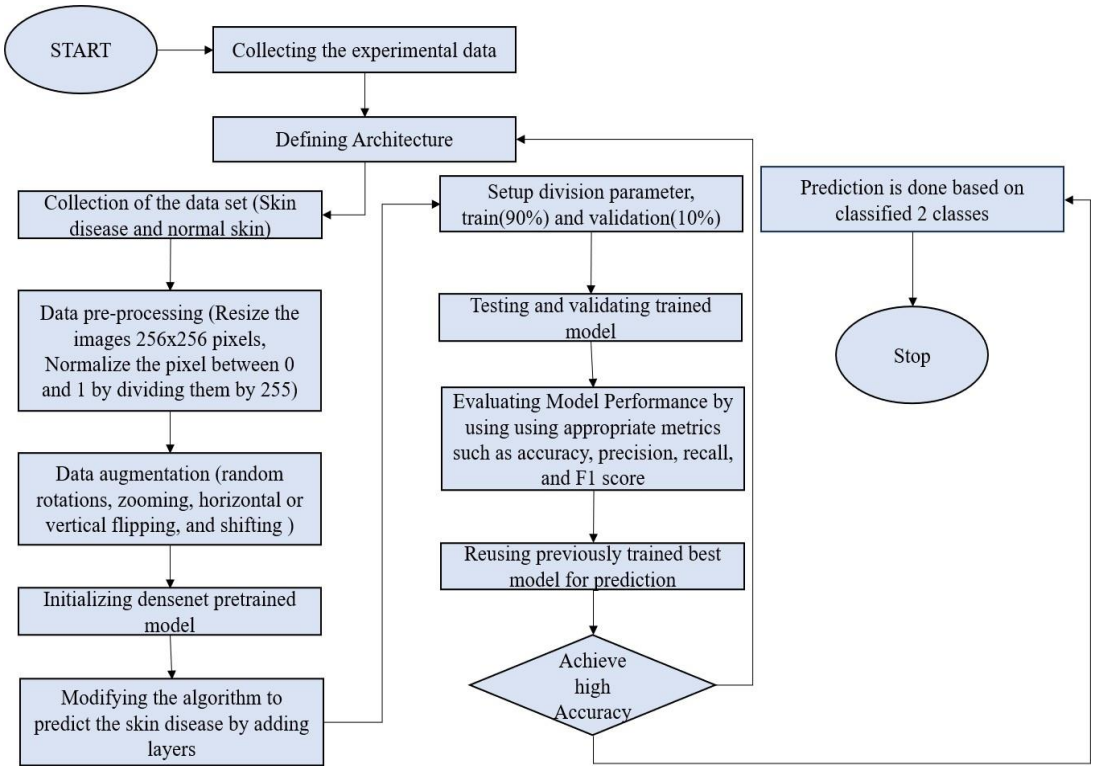

Fig 4.1 Implementation

5. Algorithm

A DenseNet is made up of transition layers after a stack of dense blocks. DenseNet 121 algorithm is the subset of transfer learning, whereas transfer learning is sub-set of deep learning.

A sequence of units make up dense blocks. Each unit generates a fixed-size feature vector and packs two convolutions, each followed by batch normalisation and REL U activations. The amount of fresh information that the layers allow to flow through is controlled by a parameter known as the growth rate.

Contrarily, transition layers are fairly straightforward parts created to execute down sampling of the features moving through the network. Each transition layer has a Batch Normalisation layer, a 1x1 convolution layer, and a 2x2 average pooling layer before it. Concatenations of all feature maps from earlier levels are provided by DenseNet, meaning that all feature maps spread to subsequent layers and are related to freshly created feature maps.

The DenseNet-121's specs are as follows: One layer of classification (16), five levels of convolution and pooling, three layers of transition (6,12,24), and two layers of denseblock (11 and 33 conv). The output layers (Ith) of conventional CNNs are typically calculated by applying a non-linear transformation (HI(.) on the output of the preceding layer XI-1). (1) XI = HI (XI-1) DenseNets concatenate rather than add the layer output functionality maps to the inputs. An simple communication model for enhancing information flow across layers is provided by DenseNet: The characteristics of all preceding layers provide input to the Ith layer: The equation is then rewritten as XI = HI ([X0, X1, X2,.....XI-1,]). (2) Where a single tensor [X0, X1, X2,... XI-1,] is created by concatenating the four tensors of the preceding layers' output maps. Batch normalisation, activation (ReLU), and convolution are the three main procedures that make up this function. The newly designed DenseNet offers benefits including feature reuse and a reduced risk of either gradient bursting or disappearing.

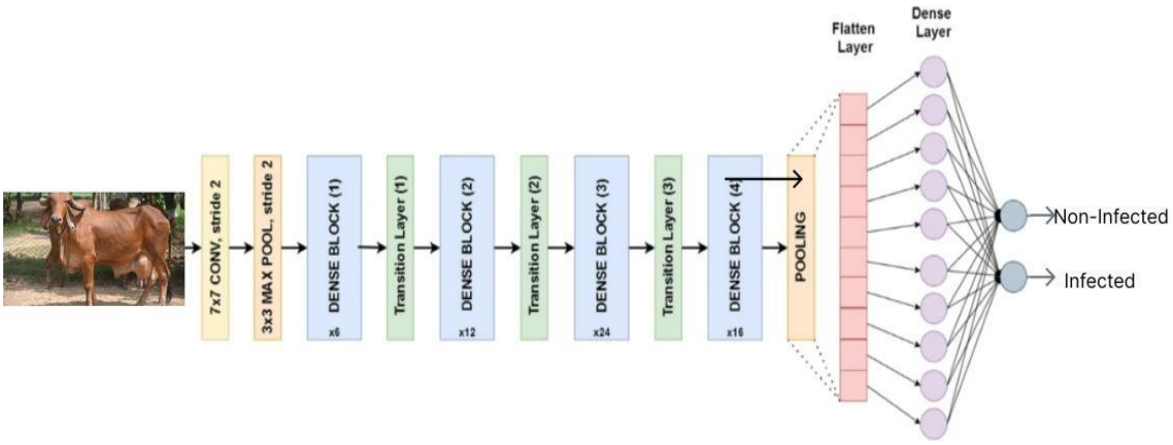

Fig 5.1 : Algorithm

6. Output screens

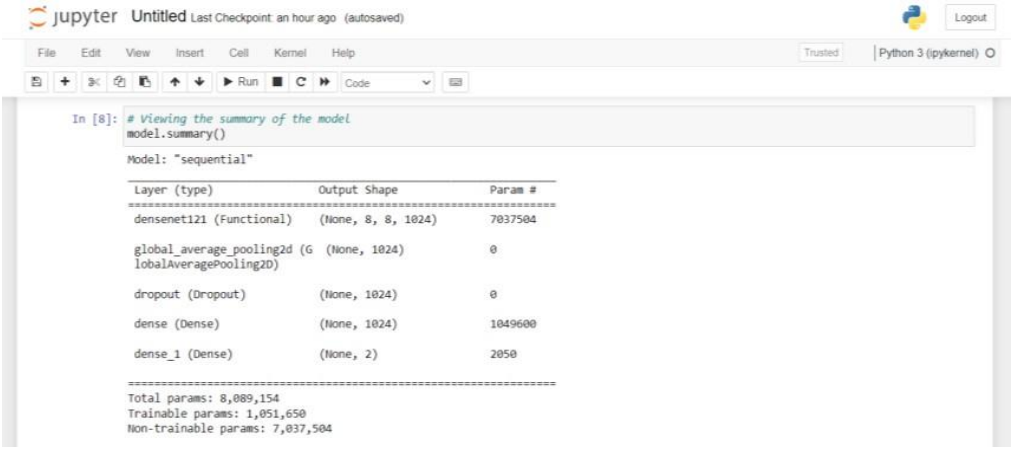

Fig 6. 1: Model Summary

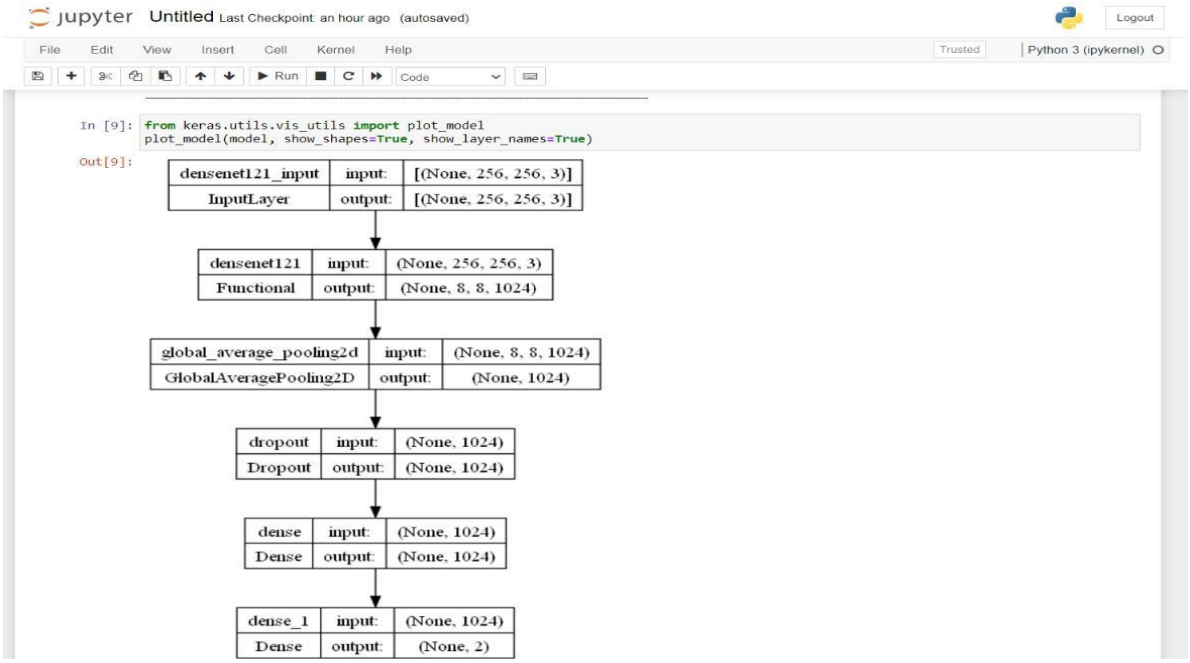

Fig 6.2: Model Plot

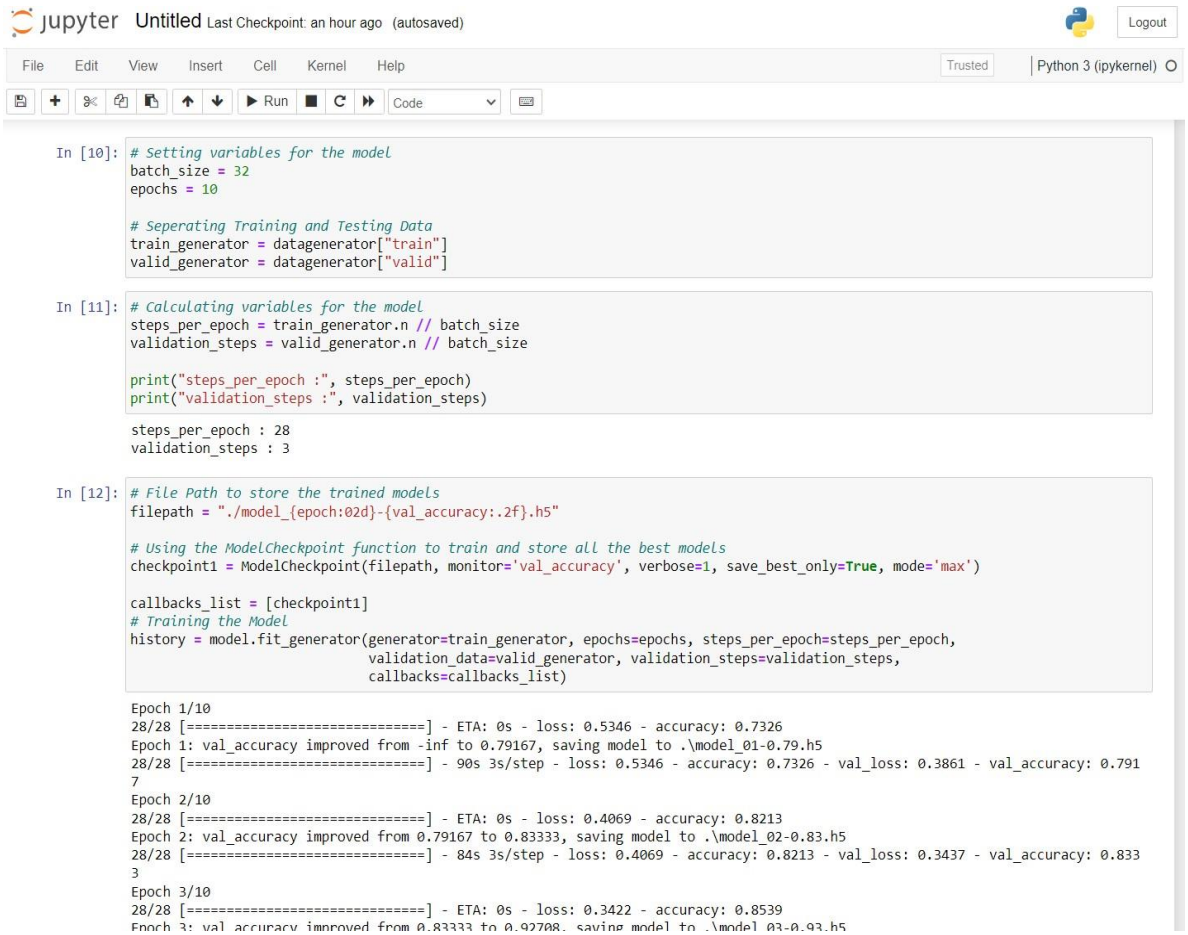

Fig 6.3: Model Building and Training

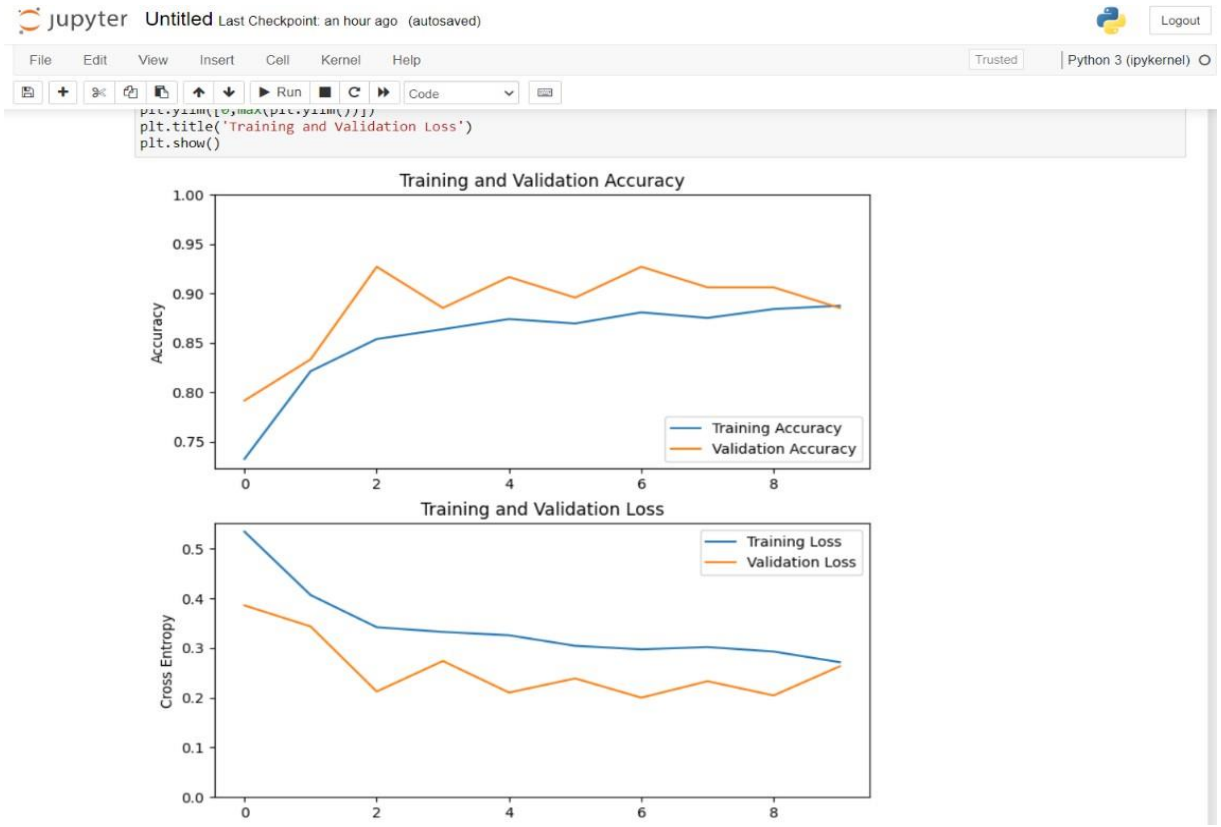

Fig 6.4: Model Accuracy and Model Loss

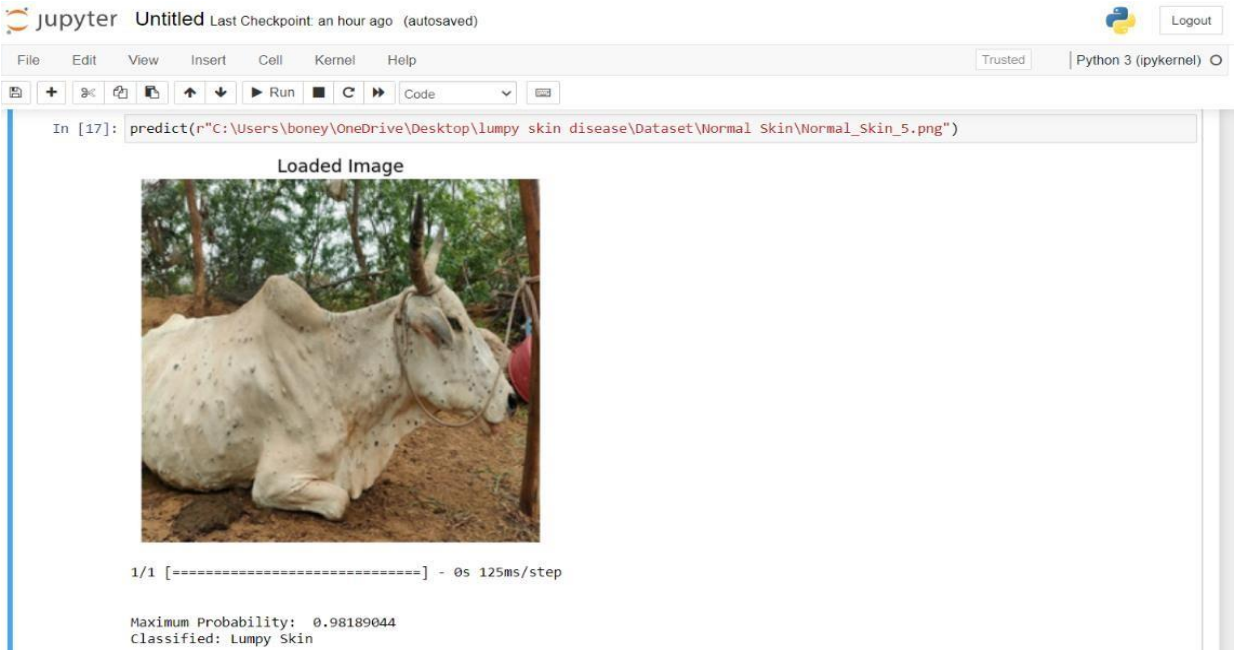

Fig 6.5: Prediction of Lumpy Skin Disease

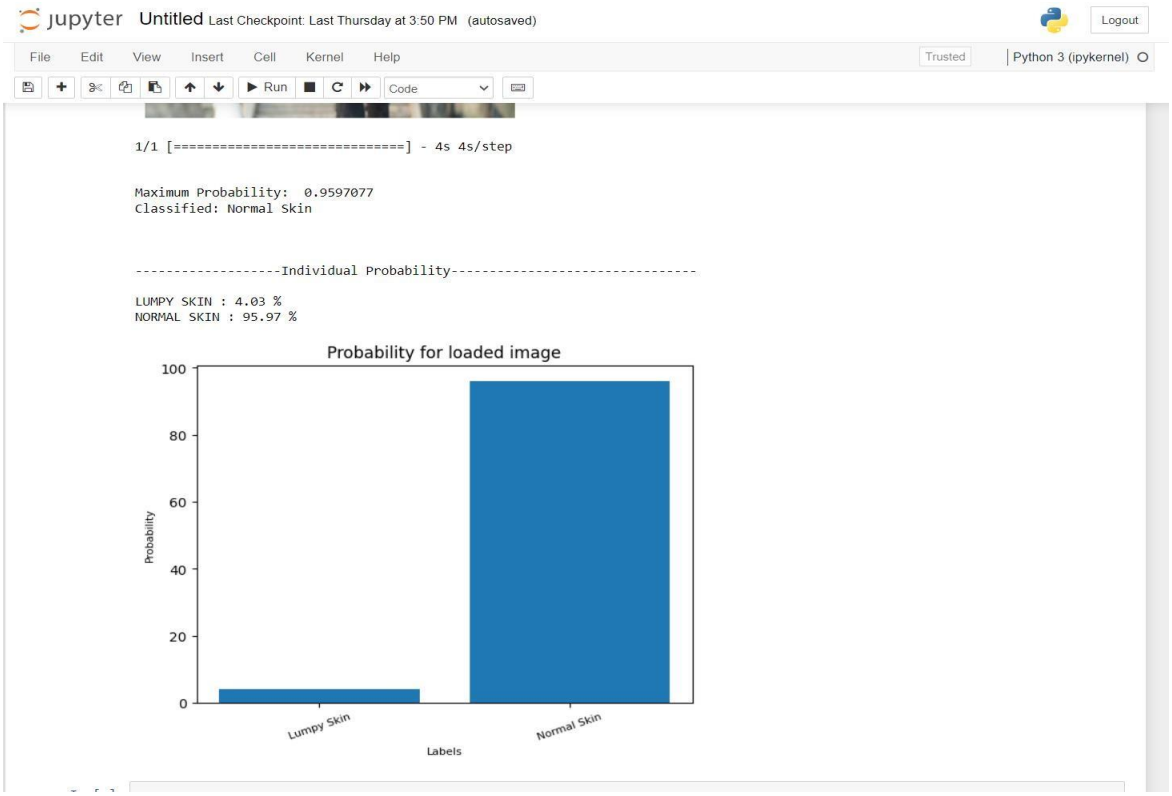

Fig 6.6: Individual Probability of Lumpy Skin

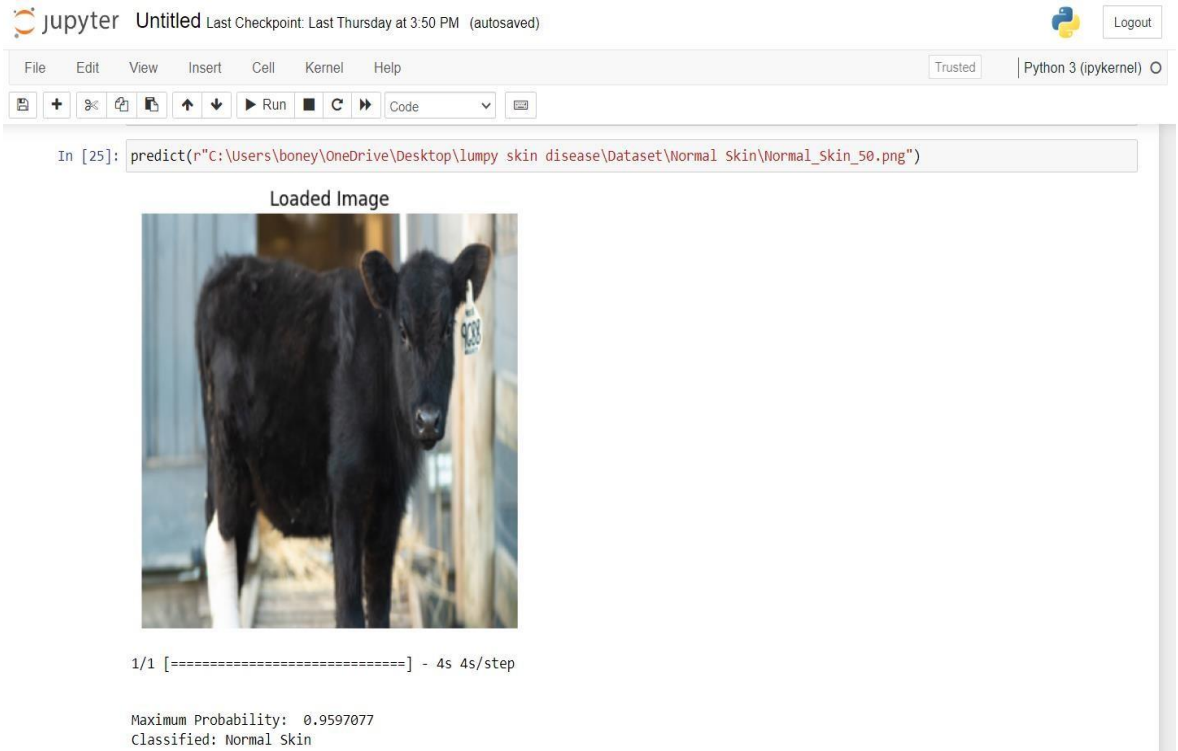

Fig 6.7 : Prediction of Normal Skin

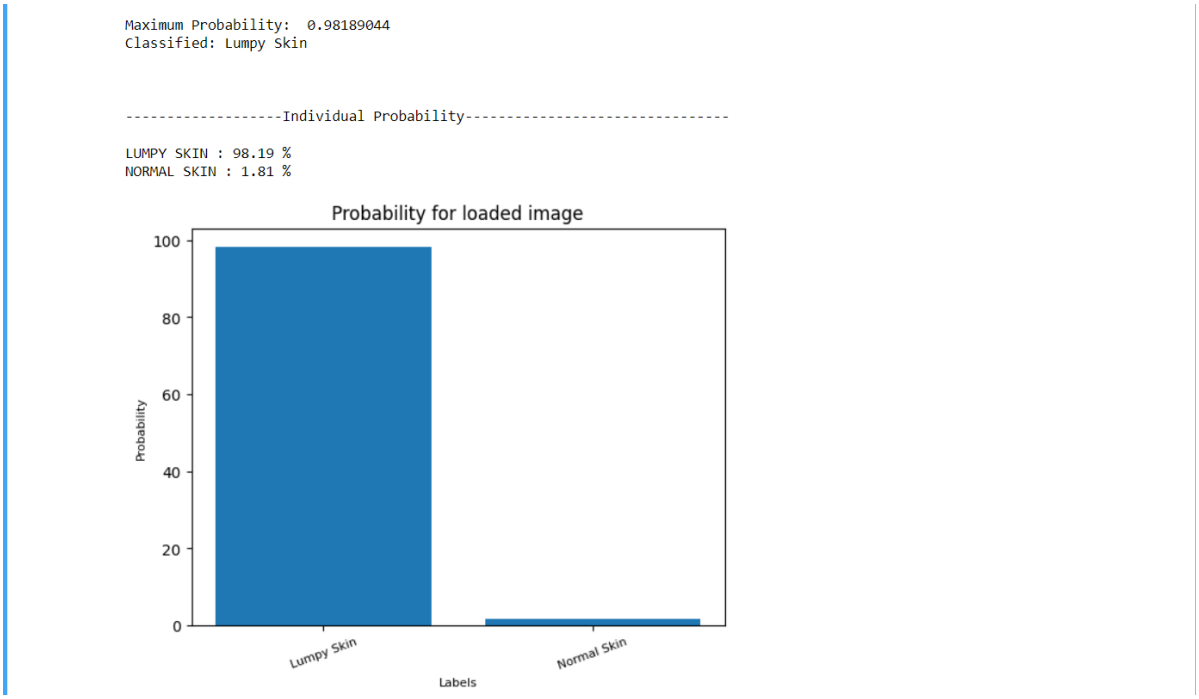

Fig 6.8 : Individual Probability of Normal Skin

7. CONCLUSION

There has been much study on the classification of skin conditions affecting humans but the categorization of skin disorders that affect animals has received less investigation. We created a system in this study to distinguish between animals with lumpy skin disease and those whose normal skin is unaffected in order to identify and categories them. One contribution of this study is the development of lumpy skin disorders utilizing image processing and machine learning approaches.. This technique has a high degree of accuracy in identifying lumpy skin conditions. Recording a real-time picture rate, which is strongly related to the number of infected instances, might be useful given that improving the dependability of the suggested computational technique for testing could be advantageous.

8. FUTURE ENHANCEMENT

In the future, there are several potential enhancements that can be made to the lumpy disease detection system. One possible enhancement is the integration of IoT devices such as cameras or sensors. This integration would enable real-time data capture from cows, facilitating continuous monitoring for lumpy skin disease.

Developing a mobile application could provide users with a convenient way to upload images for analysis and receive real-time results.

Integration with existing electronic health record systems used in veterinary clinics or farms is another potential enhancement.

Continuously updating and refining the classification models is another important future enhancement. This could involve incorporating new data and leveraging advanced deep learning techniques.

These future enhancements aim to improve the functionality, accessibility, and accuracy of the lumpy disease

detection system. By incorporating IoT devices, real-time monitoring, mobile applications, integration with existing systems, advanced classification models, automated reporting, and collaboration platforms, the system can provide more comprehensive and efficient disease monitoring and control measures for lumpy skin diseasecows.

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