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Animal Detection and its Disease Prediction by Neural Network Classifier

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Abstract: In this Project highly accurate and high-speed face detection method from the images that exactly find the pets (dog and cat) in the image. Our method achieves accurate detection performance by constructing an effective detection dictionary based on Machine learning using features extraction and neural network. After detecting the animal, the classifier will predict whether the animal affected by any disease. Once the animal is classified with disease, the motor shuts the door not allowing the animal to enter, when the animal is not identified with disease and if classified normal then the motor opens the door to let the animal inside. The accuracy of diagnosis is comparatively related to the medical skill. To find the great rate, and accurate diagnosis of animal disease. In this Project the model is able to carry out animal disease's diagnosis more approximately and have good prediction on the condition of small samples and provide a new approach for animal disease diagnosis.

Keywords: Face detection method, Machine learning, Animal disease diagnosis, BPNN, Image Processing.

I. INTRODUCTION

Animals are prone to skin diseases if not treated properly. It can happen because many bacteria and fungi attached to the skin of animals are not treated properly. Skin diseases in animals have diverse causes as well as diverse types of the consequences, and early diagnosis are diverse. Forward chaining itself is data-driven because the inference starts from the available information and is then inferred. Certainty Factor uses a definite or uncertain hypothesis method that uses metrics, whereas, forward chaining uses data driven from available information and after that comes the conclusion. With both methods designed to determine the early diagnosis of cat disease. Some diverse symptoms and conclusions, as well as hypotheses obtained from medical experts, are used to diagnose the onset of cat skin disease symptoms.

II. RELATED WORKS

T. Nordseth et al., "Clinical state transitions during advanced life support (ALS) in in-hospital cardiac arrest," Resuscitation, vol. 84, no. 9, pp. 1238–1244, 2013. When providing advanced life support (ALS) in cardiac arrest, the patient may alternate between four clinical states: ventricular fibrillation/tachycardia (VF/VT), pulseless electrical activity (PEA), asystole, and return of spontaneous circulation (ROSC). At the end of the resuscitation efforts, either death has been declared or sustained ROSC has been obtained. The aim of this study was to describe and analyze the clinical state transitions during ALS among patients experiencing in-hospital cardiac arrest[1]. E. Skogvoll et al., "Dynamics and state transitions during resuscitation in out-of-hospital cardiac arrest," Resuscitation, vol. 78, no. 1, pp. 30–37, 2008. The state or rhythm during resuscitation, i.e. ventricular fibrillation/tachycardia (VF/VT), asystole (ASY), pulseless electrical activity (PEA), or return of spontaneous circulation (ROSC) determines management. The state is unstable and will change either spontaneously (e.g. PEA → ASY) or by intervention (e.g. VF → ASY after DC shock); temporary ROSC may also occur. To gain insight into the dynamics of this process, we analyzed the state transitions over time using real-life data[2]. M. Frikha, E. Fendri, and M. Hammami, "People search based on attributes description provided by an eyewitness for video surveillance applications," Multimedia Tools and Applications, vol. 78, no. 2, pp. 2045–2072, 2019. A number of supervised learning methods have been introduced in the last decade. Unfortunately, the last comprehensive empirical evaluation of supervised learning was the Statlog Project in the early 90's. We present a large-scale empirical comparison between ten supervised learning methods: SVMs, neural nets, logistic regression, naive bayes, memory-based learning, random forests, decision trees, bagged trees, boosted trees, and boosted stumps. We also examine the effect that calibrating the models via Platt Scaling and Isotonic Regression has on their performance. An important aspect of our study is the use of a variety of performance criteria to evaluate the learning methods[3]. H. Galiyawala, K. Shah, V. Gajjar, and M. S. Raval, "Person retrieval in surveillance video using height, color and gender," in 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pp. 1–6, IEEE, 2018. A person is commonly described by attributes like height, build, cloth color, cloth type, and gender. Such attributes are known as soft biometrics. They bridge the semantic gap between human description and person retrieval in surveillance video. The paper proposes a deep learning-based linear filtering approach for person retrieval using height, cloth color, and gender. The proposed approach uses Mask R-CNN for pixel-wise person segmentation. It removes background clutter and provides precise boundary around the person. Color and gender models are fine-tuned using AlexNet and the algorithm is tested on SoftBioSearch dataset. It achieves good accuracy for person retrieval using the semantic query in challenging conditions[4]. V. Gajjar, A. Gurnani, and Y. Khandhediya, "Human detection and tracking for video surveillance: A cognitive science approach," in IEEE International Conference on Computer Vision Workshop, pp. 2805–2809, 2017. Human detection has been playing an increasingly important role in many fields in recent years. Human detection is a still challenging task because, for the group of people, each individual has his unique appearance and, body shape. Compared with the traditional method, the deep learning neural network has the advantages of shorter computing time, higher accuracy and easier operation. Therefore, deep learning method has been widely used in object detection. The current state of art in human detection is RetinaNet. Among all the deep learning approaches, RetinaNet gives the highest accuracy of human detection (Lin, Goyal, Girshick, He, & Piotr Dollar, 2018).The temporal component of video provides additional and significant clues as compared to the static image. In this paper, the temporal relationship of the images is utilized to improve the accuracy of human detection. Compared to using only an image, the accuracy of human detection is 21.4% higher when a sequence of images is applied[5].E. Bernardis and L. Castelo-Soccio, "Quantifying alopecia areata via texture analysis to automate the salt score computation," in Journal of Investigative Dermatology Symposium Proceedings, vol. 19, pp. S34– S40, Elsevier, 2018. Quantifying alopecia areata in real time has been a challenge for clinicians and investigators. Although several scoring systems exist, they can be cumbersome. Because there are more clinical trials in alopecia areata, there is an urgent need for a quantitative system that is reproducible, standardized, and simple. In this article, a computer imaging algorithm to recreate the Severity of Alopecia Tool scoring system in an automated way is presented. A pediatric alopecia areata image set of four view-standardized photographs was created, and texture analysis was used to distinguish between normal hair and bald scalp. By exploiting local image statistics and the similarity of hair appearance variations across the pediatric alopecia examples, we then used a reference set of hair textures, derived from intensity distributions over very small image patches, to provide global context and improve partitioning of each individual image into areas of different hair densities. This algorithm can mimic a Severity of Alopecia Tool (score) and may also provide more information about the continuum of changes in density of hair seen in alopecia areata[6].

III. PROPOSED SYSTEM

The main steps of the proposed system were detecting the animal and identifying its disease. It consists of image processing techniques such as preprocessing, transformation, feature extraction, and disease classification. By applying this series of image processing techniques, it is possible to automate the procedure of disease identifications. Its most serious limitation is the reliance on the performance of a human operator for diagnostic accuracy. This is pursued by developing a digital image processing system to automate the examination of animal diseases. The system must differentiate the types of animal.

IV. PROPOSED ARCHITECTURE

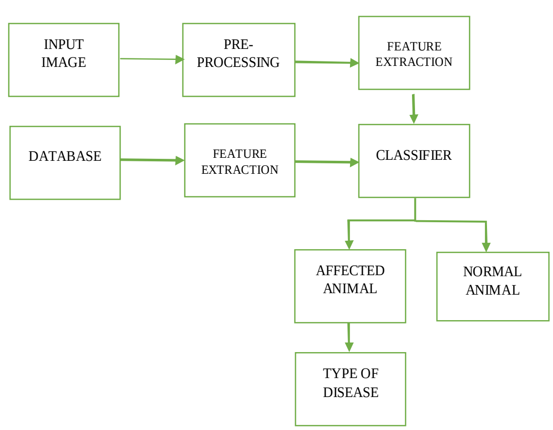

Figure 1. Block diagram for prediction of disease in animal

V. METHODOLOGY

A. BPNN

Consider a network has an input x and network function F. The derivative F'(x) is computed in two phases:

Feed-forward: the input x is given into the network. The derivatives are stored.

Back propagation: The constant is fed into the output unit and the networks run backwards. Incoming information to a node is added and the result is multiplied by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected is the derivative of the network function with respect to x.

B. PNN

PNN is a learning algorithm used for training the artificial neural network. Mainly, the propagation neural network algorithm consists of two stages i.e. — forward pass and backwards pass through which various layers or sections of the network are trained.

The algorithm for PNN can be given as follows: 1. The first step is to initialize the weights randomly. 2. In second step, an input vector pattern is provided to the network. In the block diagram represents input image of animal disease sample images can be the given to the system.

In the preprocessing stage it will remove the noise by using filter, and then it sends it to Wavelet transform and GLCM for features extraction from the input image. Also, this used extract the features. Database are loaded into Neural Network, given features values are send to the NN. It will classify the animal disease finally.

VI. MODULE DESCRIPTION

A. Preprocessing

Images preprocessing is the term for operations on images like changing the RGB image to a gray one by adjusting the resolution of the image as needed. These operations don't increase image information content, however they decrease it if entropy is associate degree metric. The point of preprocessing is partner degree improvement of the picture data that stifle undesirable twists or upgrades some picture choices pertinent for more procedure and investigation task.

B. DWT

Positional Ternary Pattern (PTP) assigns eight-bit computer code to every element of a picture. Initially, Kirsch compass masks computes the sting response of eight neighborhood pixels. Then, we tend to choose the first and secondary direction from those edge responses. Here, we tend to take an extra step to pick out the secondary direction in such a way that, it will represent higher corner structure of that element. At last, we tend to introduce a ternary pattern of the first direction that distinguishes the flat and edge-based region.

C. Feature Extraction

The image which is received as input can be transformed into a reduced set of features. The features may contain the information from the input data, due to which the desired task can be performed by using this reduced amount of data instead of the initial unaltered data. Human features are a form of fixed features directly extracted from images. Divergent from these, deep neural networks recognize features from images, and determine multiple levels of representation, with higher-level features depicting more abstract characteristics of the data.

D. Classifier

Neural networks are predictive models are based on the action of biological neurons. The selection of the name "neural network" was one of the greats PR successes of the Twentieth Century. It sounds more than a technical description. However, despite the name, neural networks are far from "Artificial Brains." A typical artificial neural network have a hundred neurons. In comparison, the human nervous system is believed to have about 3×1010 neurons. We are still lighting years from "data." The original, "Perception" model was developed by Frank Rosenblatt in 1958. Rosenblatt's model consist of three layers, (1) a "retina" (2) "association units"(3) "the output layer." A critical analysis of perceptions published in 1969 by Marvin Minsky and Seymore Papert pointed out a number of critical weaknesses of perceptions, and, for a period, interest in perceptions waned. "Learning Internal Representations by Error Propagation was published by " David Rumelhart, Geoffrey Hinton and Ronald Williams. They also provided an effective training algorithm for neural networks.

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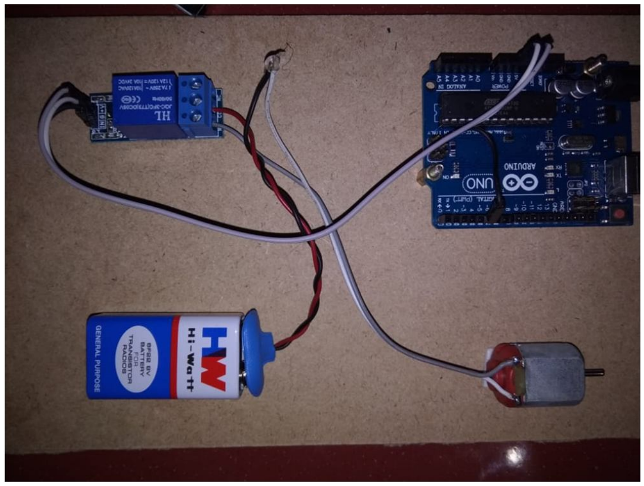
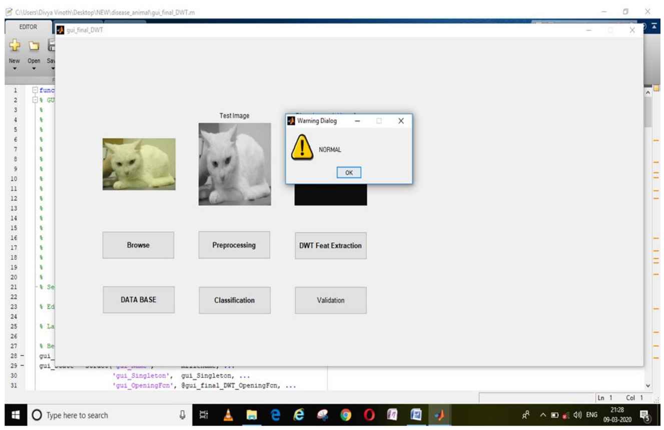
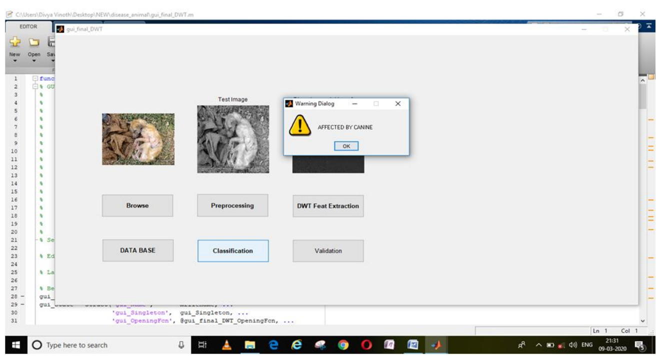
VII. RESULTS







VIII. CONCLUSION

This project developed a motion adaptive animal chamber which is controlled by an image classifier to maintain the head of a freely moving rat near the center of the Neural Network is based on its head position measured by a pair of motion trackers. A pilot validations experiment demonstrated that the motion adaptive animal chamber increased the time the animal's head spent within from 10% without motioning compensation to 88% after motion compensation. The ability of the animal chamber to keep a freely moved an animal within the micropetfov depends strongly on the animal's behavior. In general, nfor low activity behavior types (sleeping and low-to-medium activity), compensation can be expected to result in the head being located within the FOV approximately 90% of the time. Options for improving the performance of the motion adaptive animal chamber will be explored with emphasis on improving the compensatory motion of the system for high activity behaviors. Other future work includes refining our motion in tracking technique, developing attenuation correction strategies and performing pilot studies of freely moving animals undergoing micro PET imaging studies.

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