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Dog Identification AI System: A tool for identifying the presence of dogs in an image

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Images have long been used in the field of forensics because of the data that they are capable of capturing. Automatic digital image generation is incredibly common in the modern age and this has provided the scientific community with plenty of use cases for applying algorithms that allow information to be extracted from an image through machine learning. Recognizing the value of the data that could be retrieved from an image, researchers have experimented with novel image recognition software, causing ethical concerns to be raised about the intention of this kind of software and how it is practically applied (Clark et al., 2009). The specific use case that is the focus of this paper is the application of machine learning to identify if an image contains none, one, or many dogs. One implementation of this use case is presented, along with research and technology that has been used for existing implementations. The problems addressed by software that focuses on this use case are also presented, along with insights into how this kind of software can be extended to solve other issues.

Image analysis is an area of significance within many fields of research, as its applications are seemingly endless. This is due to the problem-solving capabilities that the data gathered during image analysis has. The problem of properly evaluating the status of an ecological environment can be resolved through the application of image recognition and analysis software (Brodrick et al., 2019). Due to natural reasons, it can be impossible for ecologists to gather adequate data to understand the environment of a particular area they are researching. To make the process more efficient, researchers have begun to use trap cams that automatically capture wildlife activity at all times (Reeder, 2020). These images can then be analysed to evaluate aspects of the present ecological environment, improving the scientific community's understanding of a geological area and allowing them to make well-informed decisions regarding this location. There are various approaches that have been taken in the past to accurately and efficiently identify wildlife and their numerous attributes that can affect an ecological community.

Two primary approaches are typically taken to evaluate images containing objects of particular interest. The more traditional of the two utilizes the eyesight of human individuals to determine the information in the image that is desired. In more recent years with the development of modern AI and machine learning, another approach has been to use neural networks and deep learning to develop software that can intelligently evaluate relevant data within images (Brodrick et al., 2019). The latter approach is of clear interest, as it theoretically allows for more efficient and precise image analysis and can be further developed in the future to serve more complex use cases. Relying on humans to provide image analysis allows for natural inaccuracies and biases to arise due to inevitable human imperfection when performing analysis. This can cause unreliable resulting information generated from the analysis, which could effectively make the entire analysis obsolete. Human analysis is also limited to an individual's cognitive speed, whereas using technology for analysis allows researchers to take advantage of the speed of modern processors. While automating the process of image analysis can avoid limitations imposed by human analysis, it is not without its own issues. To train image analysis software, existing data must be supplied. This data could possibly be a result generated by a faulty or biased algorithm. It could also be data assembled by a human, leading to their individual biases potentially being represented within the data. If working with flawed data, the algorithms used for analysis may not function as intended, producing a faulty analysis in the process. Thus, both approaches have similar pitfalls, as there are many points within each system where bias may be inserted.

The specific implementation provided for this paper makes use of the tech-based approach of image analysis, using machine learning and a neural network to precisely identify the presence of a dog or multiple dogs within various images. This software is designed with the sole intention of identifying dogs and not other forms of wildlife, allowing dogs and their several interesting data points to be a focal point of image analysis. The primary dataset used to train the implementation discussed is from Stanford University and consists of 20,580 images of different dogs (Khosla, et al., 2011). The technical architecture of the solution is presented below in Figure 1.

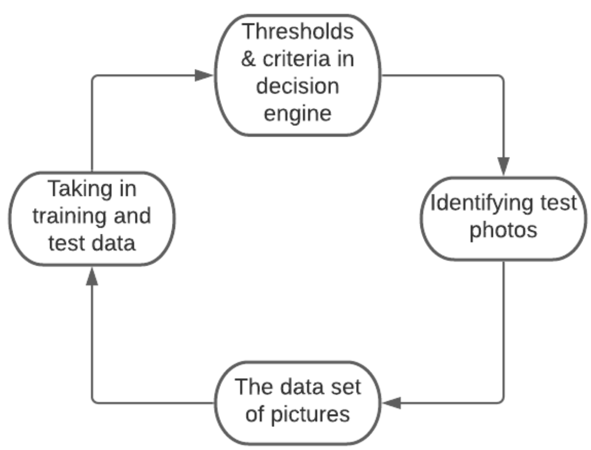

Figure 1. High level architectural diagram of the presented implementation. This diagram describes how the training data is used to train the model along with how the model is used to evaluate test data within the presented implementation.

Essentially, the implementation heeds by the following ordered processes to accomplish image analysis. First, the training data is read into the application using the TensorFlow_Dataset library from Tensorflow. During this process the data is normalized to contain values between 0 and 1 and the training data has 20% stripped away for validation. Next, this training and validation data is used to create a neural network model. The model is built in the Keras library from TensorFlow and uses the Keras-Tuner library to determine the hyperparameters. This model is created based on the training data used, and is therefore subject to the faults and biases contained within the training data. Then, The testing data is read into the application. Finally, the network model is used to classify the testing data into images containing one or many dogs and images containing none. The entire process is administered by a singular file, TestNN.py. It is important to note that TensorFlow is present in several modern image analysis software that implements a deep neural network, where its efficacy has been routinely demonstrated (Abadi et al., 2016). The file structure of the software is provided in Figure 2.

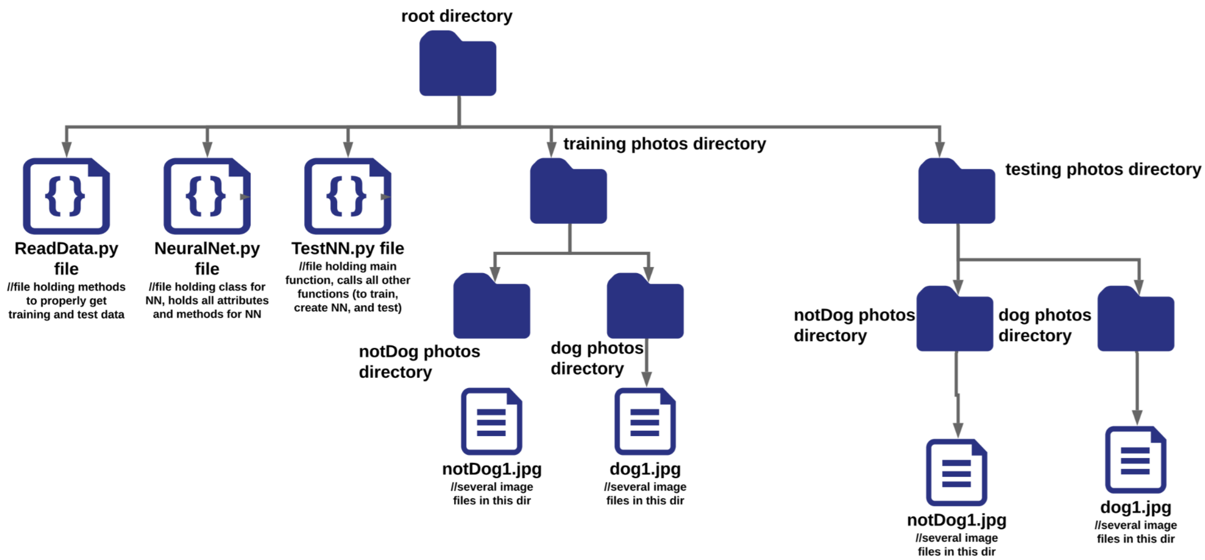

Figure 2. File structure diagram for presented implementation.

The data within the training dataset is quite diverse. It includes images of nearly every breed and color, along with images that contain more than one dog and images with dogs in varying positions. In its current iteration, the solution is able to determine what images have dogs and which don't even with the variables present within the training dataset at about 73% accuracy. We suspect that there may be some differences in the not dog test images and validation images which accounts for the difference from the about 82% accuracy of the validation data. Extending the implementation to allow for functionality to classify dogs differently based on color, breed, and relative size is a logical next step for improving this solution. Retrieving the exact location of each dog in an image is also not a present function within the current iteration, but with the potential application this feature presents, it will be pursued in future iterations. The implementation as it currently works represents a foundational iteration in an AI software that can properly recognize different forms of wildlife.

The eventual purpose of this particular image analysis implementation is to aid in the acquisition of important wildlife data associated with a specific ecological environment. In order to properly understand all impacts of this software, it is important to critically think about the ways this software can be used in an unethical manner. A primary concern is that this kind of software may not be used with the intention of improving the life of wildlife within an environment, but instead to harm it. The conclusions of the image analysis may allow for more efficient hunting or it could be used to serve as a justification for the need to hunt within a specific area. Obviously, this can disrupt the environment as well as lead to species endangerment or eradication, which is a great concern. Unfortunately, there is nothing inherent in the development of this type of software that can restrict the likelihood that it is used to harm the wildlife that data is gathered from. Another concern displays itself when evaluating the economic impacts that the use of this software can have. Currently, it appears that the only method used to protect against wildlife damages is through private wildlife insurance whose premiums typically rise as the prevalence of wildlife in an area rises (Gren et al., 2018). Given that this software allows for a comprehensive outlook of the wildlife present within an environment, it is logical to assume that it could be used to justify raising insurance prices for landowners. Existing policies relating to this insurance have proved controversial and are in clear need of improvement, so supporting the prevalence of these policies may be of ethical concern.

Images can contain lots of relevant information, leading to automated forensic image analysis of becoming very popular in recent years. Recognizing the flaws in human analysis, software can be built to more efficiently and precisely extract and analyze specific image data. It was demonstrated through one particular implementation how a neural network and deep learning can be utilized to build a desired application that could classify images that don’t contain dogs and those that do. This solution can be further worked upon so that it can do image analysis on wildlife in general, similar to existing implementations. While this software is created with the intention of being used to help the wildlife and human population that lives within an area, it is important to be cognisant of how the software could be used in an unethical manner. Through analysis of the various consequences of implementing this kind of software, one is able to see the potential it has for advancing our understanding of an ecological environment while also making one aware of the inevitable unethical uses of the software. In conclusion, the implementation presented is an imperative step in building a larger solution that can serve the scientific community by providing image analysis of various forms of wildlife, and it is important to recognize the ethical impacts that this software can have as it continues to be developed.

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