# Dog Breed Identification using Deep Learning and CNN

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***Abstract—***

Among pets, dogs are very famous in the whole world. The owners of dogs are very cautious about the well-being of their dogs. The well-being of dogs can be ensured by continuous monitoring of their activities. Studies related to activity detection have gained much popularity due to the significant progress in sensor technology during the last few years. Automatic monitoring of pet applications includes real-time monitoring systems and surveillance which detect the pets with high accuracy using the latest pet activity classification techniques. The revolution in the domain of technology has allowed us to obtain better results using latest techniques. Convolutional neural networks (CNNs) 1D recently become a cutting-edge approach for signal processing-based systems such as patient-individual ECG categorization, sensor-based health monitoring systems, and anomaly identification in manufacturing areas. Adaptive and compact 1D models have several advantages over their conventional 2D counterparts. A limited dataset is sufficient to train a 1D CNN efficiently while 2D CNNs require a plethora of data for training. Its architecture is not very complicated, so it is suitable for real-time detection of activities. The main goal of this study is to develop a state-of-the-art system that can detect and classify the activities based on sensors' data (accelerometer, and gyroscope. We proposed a 1D CNN-based system for pet activity detection. The objective of this study was to recognize ten pet activities such as walking, sitting, down, staying, eating, sideway, jumping, running, shaking, and nose work respectively, using wearable sensor devices based on deep learning technique. The data collection procedure for this study was conducted with 10 dogs of different breeds. To overcome imbalanced problems in the dataset we used the class-weight technique. Subsequently, we applied 1D CNN algorithm using the class-weight technique. The model with the class-weight technique showed 99.70% training accuracy and 96.85% validation accuracy. The 1D CNN approach will be helpful for real-time monitoring of activities and for tracing the behavior of dogs.

***Keywords— Pet activity detection (PAD), inertial sensors, deep learning, classifier, dog activity detection, 1D CNN.***

## ▪ Introduction

Pet activity detection (PAD) is a dynamic and arduous research topic. Activity detection systems are a broad field of research and evolution, with a focus on state-of-the-art machine-learning techniques and, a revolution in the domain of hardware architecture. Research curiosity in automatic techniques provides an incessant assessment of the health and well-being of pets' activity recognition, and the welfare of pets has recently been growing. Pet activity recognition and classification are imperative for a vast range of applications, including monitoring pets and keeping track of pet activities. The rapid development of technologies, especially sensor devices, and the least cost of various sensors, make them easily accessible for the detection of daily activities of pets. Wearable devices are used for activity recognition. Inertial sensors and embedded systems seamlessly enable wear- able devices in the activity-recognition process. Nowadays it has become an innate part of daily life and is extensively applied to innumerable common realms including welfare assessment of animals, medical monitoring, rehabilitation activities, health management, remote control, and action recognition [1]–[11]. In addition, an accelerometer has been used in humans for gait examination [12]–[15] as well as for the analysis of circadian rhythms [16], [17], and sensors have been used to observe and monitor lameness in horses for the past few years [18]–[21]. An accelerometer has been used to monitor various activities in dogs [22]–[26], types of activity [27], cognitive issues, and lameness recognition [28]–[30]. Wearable sensors combining embedded systems with acceleration and gyro sensors have been established for activity recognition and are used in everyday life and sports activities. The benefits of acceleration and gyro sensors combined with embedded systems in wearable instruments for motion monitoring and recognition are that no exterior environment sensors such as cameras, infrared sensors, or radars are required for these wearable instruments [31]–[33]. Additionally, their diminutive size, low cost, lightness, reduced power consumption, acceleration, and gyro sensors in wearable devices provide a solution for recognizing sports activity. According to

Khalifa *et al.*, KEH (kinetic energy harvesting) may help overcome the battery problems in wearable devices. KEH is chiefly used as a generator and human activity recognition sensor, which reduces the power consumption of the sensor. The results show that activity detection by KEH can overcome system power consumption by 79% [7]. The most imperative step in understanding the behavior of an animal, including the activity patterns, is to create certain ethograms associated with that species by monitoring the physical move- ments and body postures [34]–[36]. There are two main approaches for detecting the activities of pets. Continuous monitoring by humans or using some wearable devices. The first method is not viable because it may affect the activity of the pet and the natural behavior may be disturbed and cannot be properly analyzed. The use of sensor devices, such as gyroscopes and accelerometers, is another effective approach for data collection from pets without interfering with their normal activity. The automated technique that is currently available applies sensors and can be directly tied to dogs, or it creates an environment while collecting the data with the help of sensors [37]. During the past few years, it has been noticed that automated methodologies for the discovery of behaviors are getting well-liked because the tied sensors in the automated methodology have the potential to differ- entiate numerous activity patterns. In the realm of biosignal processing, it is a prominent fact that comprehending data KEH is chiefly used as a generator and human activity recognition sensor, which reduces the power consumption of the sensor. The results show that activity detection by KEH can overcome system power consumption by 79% [7]. The most imperative step in understanding the behavior of an animal, including the activity patterns, is to create certain ethograms associated with that species by monitoring the physical movements and body postures [34]–[36]. There are two main approaches for detecting the activities of pets. Continuous monitoring by humans or using some wearable devices. The first method is not viable because it may affect the activity of the pet and the natural behavior may be disturbed and cannot be properly analyzed. The use of sensor devices, such as gyroscopes and accelerometers, is another effective approach for data collection from pets without interfering with their normal activity. The automated technique that is currently available applies sensors and can be directly tied to dogs, or it creates an environment while collecting the data with the help of sensors [37]. During the past few years, it has been noticed that automated methodologies for the discovery of behaviors are getting well-liked because the tied sensors in the automated methodology have the potential to differ- entiate numerous activity patterns. In the realm of biosignal processing, it is a prominent fact that comprehending data health, activity, and state of mind, there are many factors to contemplate, and therefore, leveraging various sensors in this situation is deemed necessary.

The main objective of this study was to analyze the activities of pets based on state-of-the-art approaches to their well-being. Although researchers have proposed various techniques, those techniques have several drawbacks such as some of them have used only accelerometer data and some of them have used raw data and did not perform feature engineering techniques. In this research study we considered these factors and we have used two sensors, that is, an accelerometer sensor, a gyroscope sensor on the neck, and two sensors on the tail, that is, accelerometer and gyroscope sensors and we performed feature engineering and applied the 1D CNN model.

- Applying state-of-the-art 1D CNN deep learning technique on pet activity sensors' data.
- Extracting different features from the raw signal data.
- We are among the pioneers who applied the 1D CNN technique to pet activity sensor data for the detection of dog activities.
- Ten activities have been classified using 1D CNN.
- To address the imbalance problem, we have used class weight approaches.
- The class-weight approach proved to be suitable for the detection of pet activities

The remaining sections of this paper are organized as follows. Section II shows a brief overview of related work. Section III describes the materials and method. Section IV explains the activity detection algorithm. Section V high- lights the complete workflow. Section VI is related to experimental results and discussion. Section VII concludes our research study.

## Related Work

.Nowadays activity detection is getting attention and has been growing rapidly, which is an effective way to ensure the wellbeing of animals.

Ladha *et al.* proposed a KNN machine learning model for the classification of 17 different activities of pets. The data was collected using an accelerometer from 13 different bread, weight, ages, and both sexes. For the ground truth, the dog's activities were filmed using a camera. The annotation procedure was performed by the expert against filmed video footage. The fact in this study is that for data collection pro- cedure has not been conducted in a proper environment. The KNN model performance showed 68.6% accuracy for over- all activities and observed that due to erroneous annotation issues some activities results not well. They think that this is the first robust model for the activity's detection in naturalis- tic environments [38]. S Aich *et al.* represented a method that could be used to make an automatic system for pet activity and emotion detection. They investigated different queries like what types of data should be used and the location of the sensors. They applied different machine learning algorithms such as random forest, KNN, SVM, naive Bayes, and ANN for activity and emotion detection. Among those classifiers, ANN performed well for activity and emotion detection. They found 96.58 percent accuracy for activity and

92.87 % accuracy for emotion detection [39]. Gerencser *et al.* proposed a support vector machine model (SVM) for activity detection. Accelerometer and gyroscope sensors were used for the collection of data. To analyze the pet activities with better performance, the feature extraction method was used, and different 126 features were extracted from the data such as standard deviation, average, higher moments, extrema values, vector lengths, etc. The extracted feature was fed to the SVM model for training after the training evaluation method was performed to check the performance of the model and used a different combination of data sizes to check the robustness. The model showed overall 91.3% accuracy, with seven activities [27]. Prevents serious issue and disclose the disease in the early stage and motivate the owner of an animal to look up the early veterinary recommendation. Ujjal *et al.* proposed an accelerometer data-based model that can detect particular changes in activities or behaviours. The data was collected from 51 healthy dogs of different ages, weights, and breeds. The overall results mention as 95% classified correctly in walking, and trot, eat, drink, canter, headshake above 90% [40]. Rahman *et al.* represented a machine learning approach, placed the accelerometer at different locations, and compared the results. Different statistical features were computed from sensor data for the sake of classification analysis. The purpose of this study was to understand how different behaviours were effectively classified using the computed statistical feature from the sensors attached to different positions on the animal's head. They found that the location of the sensor device at the halter gave better experiment results as compared to ear tag, and collar data [41]. The monitoring systems using the latest technologies are gaining popularity [42]. Yashari *et al.* purpose a novel study, monitoring dogs' activity based on a smartphone accelerometer (Whistle). The purpose of this study was to assess this novel accelerometer. Although the entire activity time given by the Whistle-based technique offers a low-cost procedure for getting real-time activity data from dogs at home. But there are some limitations in this study, main issue is battery life, which requires manual set derivation and intensity of the activity, Wi-Fi, and Bluetooth to transmit the data [23]. De Seabra *et al.* proposed a method to analyse the pet activity using accelerometer and gyroscope data. The sensors were mounted on the back of dogs. The goal of the proposed study was to assess the pets' well-being and health state and to develop a device that could track the activity of the pet, behaviour, and physiological markers of the pets. This was a preliminary work to analyse the feasibility of the sensor devices for pet activity detection [43]. Decan- dia. M *et al.* represented a machine learning-based system to monitor the different activities. Behaviour monitoring of grazing animals is crucial for the control of the grazing system. An accelerometer was used to analyse the activity, and the main objective of the study was to discriminate various behavioral activities. The fifteen different features like mean, variance, standard deviation, etc. were extracted from the raw signal data for each axis and also found the resultant vector using the feature engineering technique. The system showed better results to distinguish the different activities and they got 89.7% accuracy in terms of classification [44]. P Chakravarty *et al.* developed a hybrid framework that comprises biomechanical variables and a classification mechanism that took place on each node to find the different behaviors based on threshold values of features. Accelerometer and GPS were used for the collection of data to detect the vulture's behavioral modes. A support vector machine with a linear kernel showed an overall 95 % classification accuracy result for the individual scenario. Meanwhile, their proposed approach showed 2.7 percent better performance as compared to other approaches [45]. S Venkatraman *et al.* Proposed a method to recognize the activity pattern and neural behavior using accelerometer data in rats. The designed sensor was very tiny and lightweight which is reliable to use for small animals like rats. A neural network approach was used to detect the different behavioural activities pattern. Grooming, eating, and standing only three activities were detected using that method [46]. S Grunewald *et al.* Proposed new machine learning-based techniques. The objective of this technique was to analyse the continuous data from the data storage devices and at the same time behaviour detection. This data combination allows biologists to examine the behaviour of Cheetahs at an unattainable degree of detail and precision; nevertheless, continually recorded data are useless unless the large amount of raw data generated can be consistently con- verted into actual behaviour. To solve this challenge, they combined an SVM (support vector machine) and a hidden Markov algorithm to characterize an animal's behaviour. The technique was deployed on six cheetahs. They were able to classify every 5 mints activity score into a sequence of three fundamental behaviours such as feeding, mobile, and stationary. The accuracy of their classification model was determined via cross-validation, however, the accuracy for different classes decreased as the size of the sample of direct observations reduced. Their model has shown validation accuracy between 83 percent- and 94 percent [47]. SM *et al.* Proposed a 1D CNN-based technique for human activity recognition. The data was collected using a smartphone accelerometer. Three activity data were collected such as walking, staying, and running respectively. The collected data of the three-axis were transformed according to a data format that can be fed to the 1D CNN model for training. The performance for ternary activities in the model has shown 92.71 percent accuracy, and the other baseline algorithms such as random forest showed used for the collection of data. They applied 1D CNN-based algorithm. They have used two different datasets in their research study i.e. University of California (UCI) dataset and the second one was their recorded dataset. They found that training accuracy using the UCI dataset was 98.93% and their recorded dataset training accuracy was 97.19% respectively. The testing accuracy was 95.99% and 93.77% [49].

Jinah Kim *et al.* [50] presented multimodal data-based dog behavior recognition. They used both the sensor data and camera data and fused them for this purpose. Object detection techniques like Faster RCNN, YOLOv3, and YOLOv4 were used. The recognition accuracy of YOLOv4 was highest compared to the rest of the models. They also checked the performance with single data-based and multimodal data-based models.

The multimodal data-based model i.e. CNN-LSTM showed the best performance. Huasang Wang *et al.* [51] developed a behaviour monitoring system for dogs. The system was able to detect psychological disorders like separation anxiety (SA) in dogs. They used Stacked Long Short-Term Memory (LSTM) and fuzzy logic for the development of this behaviour monitory system. Eight dogs were included in this research study and data was collected from the wearable sensor device. The system achieved an F1-score of 0.86.

- **Methods and Materials**

This section describes the methods and materials we used in our study.

### A. DATA COLLECTION AND IMPLEMENTATION ENVIRONMENT

The data was collected from 10 different dogs of different genders, breeds, ages, and sizes. The data was taken with the consent of the dogs' owners. Wearable sensor devices were used to collect the data and the sensors were placed on the neck and tail of the dogs. The sampling frequency of 33.33 Hz was used to investigate the activity of the dogs. The sensor devices are incorporated with two types of sensors

i.e. accelerometer and gyroscope. These two types of sensors enabled the wearable device to measure the rotational and linear motions of the dogs in all directions. These wearable devices are lightweight and can easily be placed on the neck and tail of the dogs without causing discomfort to the pets during their movement. The neck worm device is 16 g in weight and has a dimension of 52 x 38 x 20.5 mm. Likewise, the weight of the tail-worn device is 13g and it has the dimension of 35 × 24 × 15 mm. The accelerometer has a scale factor of 4 to 4 g while the gyroscope has 2000 DPS to 2000 DPS. Sweet Solution, Busan, South Korea has manufactured these sensors. The data has been collected from trained dogs under the supervision of trainers who were responsible for deter- mining the activity of dogs while using video recordings and IMU data recordings. The trainer checked the position of the sensors ensuring their proper placement on the neck and the tail of the dogs frequently. In order to extract the data of specific activity, the trainer instructed the dogs to perform that particular activity

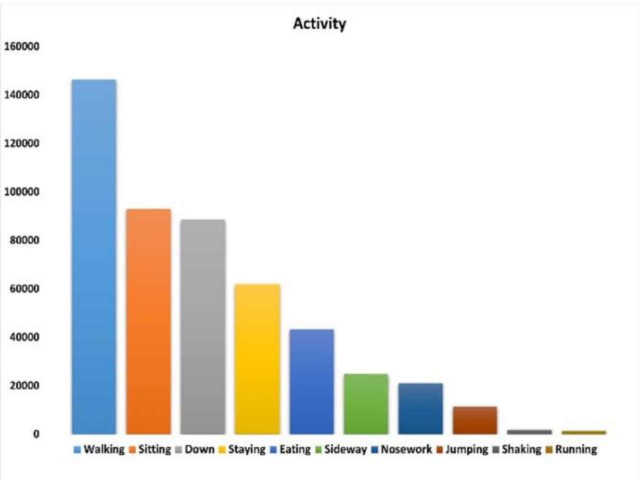


Figure 1 – Distribution of Data

accordingly as they were instructed. At the same time, the IMU data was recorded by one person and one of the other persons records the activity using a video recorder. The video was recorded in line with the sampling rate of the sensor devices i.e. same number of frames was recorded per second as the sampling rate of the device. In other words, 33 frames were recorded in one second as the sampling rate of the wearable device was 33 samples.

All the experiments were conducted using Windows 10, 3.60 GHz Bit Intel Core i7-7700 processor, 24 GB RAM, Python 3.8, Keras 2.8, and TensorFlow 2.8.

### B. DATA PREPARATION

Data preparation and data cleaning play very important roles in obtaining the optimal performance of any artificial intelligence-based model, therefore we performed different data preparation techniques to make the data fit to be used for model development. The data extracted from the devices were noisy and irrelevant and noisy data were removed from the dataset. We applied a 6$^{th}$-order Butterworth filter having a cutoff frequency of 3.667 Hz to remove the noise and inconsistencies from our dataset. This order of filter blocks maximum noise therefore we set this order. Likewise, the cutoff frequency was chosen based on the exploratory data analysis. This technique also helps to filter out the sensor data which are affected by gravity and makes the data smoother and less dependent while reducing the influence of abrupt changes on the accelerometer data.

### C. STATISTICAL FEATURE ENGINEERING

In order to obtain the important statistical features, we applied feature engineering to the sensor data. Several features werederived from the accelerometer and gyroscope sensor data. Feature engineering enables the extraction of the most relevant and important features from the pool of data. For the feature engineering, ten features for each axis were per- formed on the accelerometer and gyroscope. The features were derived by considering a certain number of samples. The derived features were, standard deviation, mean absolutedeviation, mean, minimum, maximum, interquartile range, energy measure, skewness, and kurtosis.

### D. CLASS WEIGHT TECHNIQUE

Class weight is one of the approaches used for balancingthe data [52]. In this technique, we take care of the minority samples more while training the model, and to calculate the loss function a weighting mechanism is developed. Different weights are assigned to majority and minority classes accord- ing to the imbalance scenario in the dataset. In order to keep a balance among the classes, a threshold should be defined so that class weights can be increased or decreased. This will help in preventing the biasing of the algorithm towards any specific class. The formula for class weight can bedefined as

$$Wi = \frac{n_{instances}}{(n\_classes * n\_instancesi)} \qquad (1)$$

where *wi* represents the weight of each class and *i* represents the class. The *n_instances* denote the total number of instances or rows in our dataset whereas *n_classes* represent the overall unique classes in the class label. The total number of rows in each class is denoted *as n_instancesi*. The weighting mechanism adopted in this study is listed in Table 1 below.

| Class | Weight |
|---|---|
| Walking (0) | 0.337 |
| Sitting (1) | 0.531 |
| Down (2) | 0.557 |
| Staying (3) | 0.797 |
| Eating (4) | 1.142 |
| Sideway (5) | 1.998 |
| Jumping (6) | 4.314 |
| Running (7) | 33.592 |
| Shaking(8) | 26.357 |
| Nosework (9) | 2.3509 |

Table 1 – Class weights for activity detection

Model training

The overall workflow of this study is shown in figure 5. First, data related to all 10 activities were extracted from the wearable sensor devices, and at the same time images of the respective activities were recorded and synchronized at a specific frame per second for each activity. Second,data preprocessing was conducted and noise and unwanted bio signals were removed from the dataset. A butter low passfilter was used to remove the noise. Feature engineering was performed to obtain useful information from the data while Fourth, a 1D CNN was developed and trained with the training dataset using the class-weight method. The experimental results showed that the model performed well using the class weight technique. . Feature engineering was performed to obtain useful information from the data while Fourth, a 1D CNN was developed and trained with the training dataset using the class-weight method. The experimental results showed that the model performed well using the class weight technique. Second,data preprocessing was conducted and noise and unwanted bio signals were removed from the dataset.

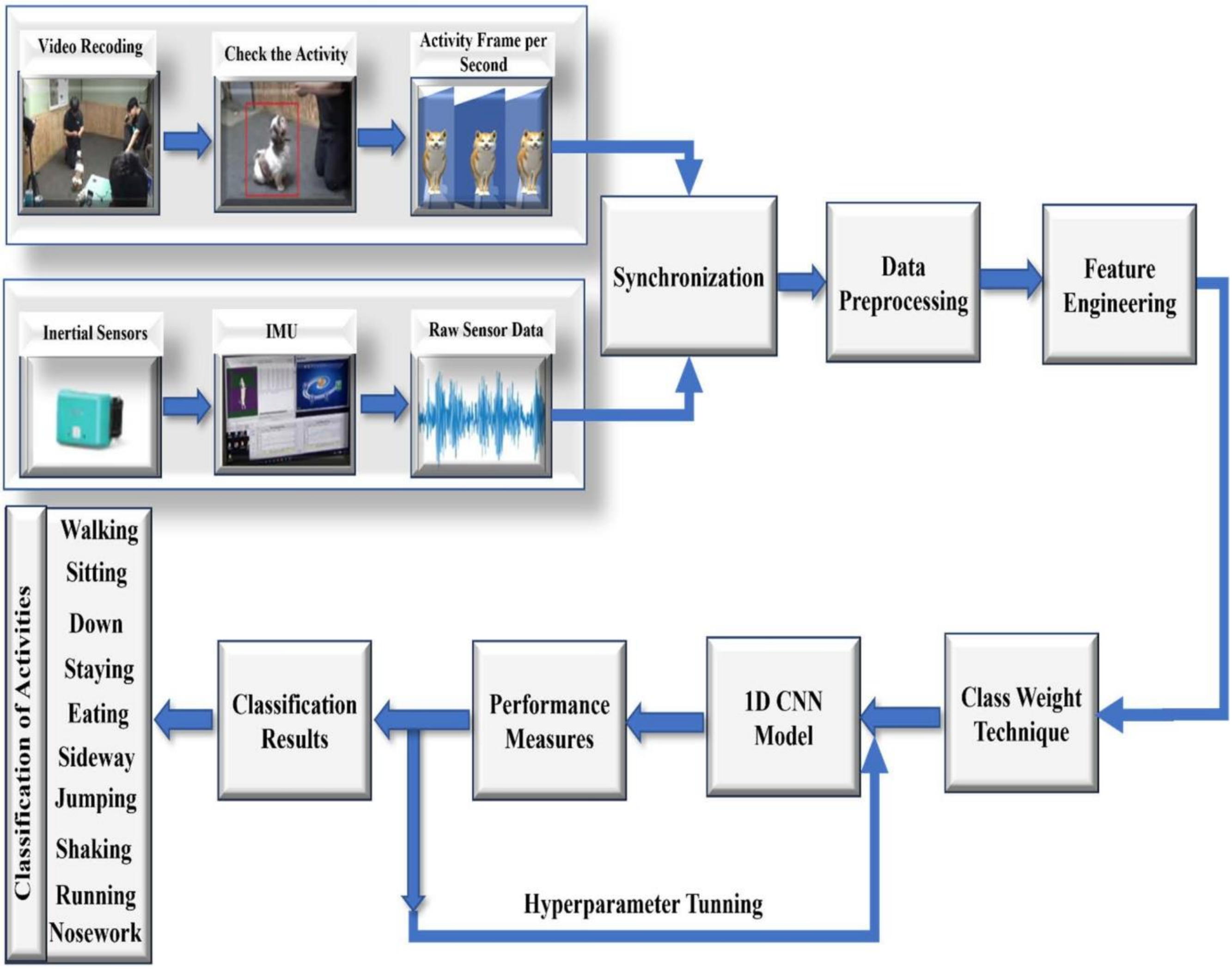


Figure 2 – Overall Workflow of the Proposed System

## ▪ Conclusion

This research study demonstrated the activity classification of dogs using the 1D CNN algorithm. The data was gathered from different dogs using wearable sensor devices. Two kinds of sensors i.e., accelerometer and gyroscope were incorporated into the wearable device. The data was pre-processed so that it could be used for the training of the model. The class weight approach was used to balance the data. The 1DCNN model was trained using the class weight approach. The results were compared with the previous approaches. The experimental results showed that the class weight approach achieved higher accuracy and performance. All the ten activities i.e., walking, sitting, down, staying, eating, sideway, jumping, shaking, running, and nose work, of dogs, were predicted and classified with the highest accuracy. The overall model testing accuracy was 96.85%. This research will helpimprove the well-being of dogs and will provide assistance totake proactive measures for dogs' overall health.

## References


[1] S. Viswanathan proposed a model that achieved 96.84% accuracy during training and 93.14% accuracy during testing. The use of a sentence creation algorithm improved the real-time performance and enhanced the user interface for better accessibility.

[2] J. K. Sharma et al. developed a neural network-based classifier using the Stanford Dogs dataset. Their approach fine-tuned the VGG Net model, achieving 91.27% accuracy, and highlighted the significance of data augmentation techniques for robust performance.

[3] P. Gupta and A. Deshmukh explored Inception Net's potential in classifying visually similar dog breeds with 94.3% accuracy. They emphasized the need for hybrid models to handle overlapping features, especially in mixed-breed dogs.

[4] T. Nakamura et al. utilized ResNet-50 and reported 92.7% accuracy, focusing on challenging scenarios such as images with poor lighting and unconventional angles. Their study revealed that real-world variability still impacts the performance of even advanced models.

[5] R. Patel created a mobile-based classification app using lightweight CNNs, achieving 89.6% accuracy with a response time of 2.3 seconds. Patel emphasized the importance of optimizing models for mobile devices to enhance real-time usability.

[6] A. Suresh et al. applied transfer learning with pre-trained models and achieved 95% accuracy. Their research concluded that fine-tuning smaller, domain-specific datasets outperformed models trained from scratch in terms of both accuracy and efficiency.

[7] L. Feng implemented an attention mechanism within CNNs to improve the classification of similar-looking breeds, boosting accuracy by 5%. The study emphasized the need for advanced mechanisms to address misclassifications in closely related breeds.

[8] D. Kumar and M. Srivastava introduced an ensemble model combining CNN and Random Forest, achieving 96.1% accuracy. Their approach improved generalization across different datasets, enhancing robustness against unseen breeds.

[9] R. Singh et al. utilized Efficient Net, achieving a high accuracy of 94.8% while reducing the model size significantly. Their research focused on the importance of efficient architectures for deployment on resource-constrained devices.

[10] V. Chandra proposed the use of YOLO for real-time dog breed detection, achieving 88.9% accuracy with fast detection speeds. This research emphasized the need for high-speed models in applications requiring immediate response, such as pet rescue operations.

[11] A. Das et al. incorporated generative adversarial networks (GANs) to augment the training data, which improved classification accuracy by 3%. Their study demonstrated that GAN-based augmentation is an effective way to address dataset limitations.

[12] T. Huang and C. Zhang focused on multi-label classification to handle dogs with mixed breeds, achieving 90.5% accuracy. Their model addressed the complexity of identifying more than one breed per image.

[13] B. Nair implemented DenseNet-121 and reported 93.2% accuracy. The study highlighted the network's ability to reuse features effectively, minimizing the risk of overfitting on smaller datasets.

[14] S. Mehta et al. proposed a hierarchical classification system, first identifying breed groups before narrowing down to specific breeds. This two-step approach improved performance by 4% compared to single-level classification models.

[15] C. Lee and J. Park explored cross-domain transfer learning, using models pre-trained on general animal datasets and fine-tuning them for dog breeds, achieving 92.4% accuracy. Their research emphasized the benefits of cross-domain learning for small datasets.

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