Project Phase 2 Report On

Dog Breed Classification and Recommendation System Using ResNet50 and Cosine Similarity

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

Computer Science and Engineering

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CERTIFICATE

This is to certify that the project report entitled ***"Dog Breed Classification and Recommendation System Using ResNet50 and Cosine Similarity"*** *is a bonafide record of the work done by* ***Alex Santhosh (U2003027), Alan Baby George (U2003019), Alen Theethai Babu (U2003026), Amal Stephen (U2003032)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

This project centers around the development of an innovative dog breeding application designed to provide comprehensive breed profiling and recommendation services. The application aims to assist dog enthusiasts and breeders in making informed decisions regarding dog breeding, acquisition, and selection based on individual preferences and lifestyle. The primary feature of the application involves a sophisticated recommendation system that uses customized profile recommendations to handle issues with cold start and breeding compatibility. Our method takes user preferences, geographical location, and breeding compatibility into account while utilizing content-based filtering for initial recommendations and incorporating appropriateness rankings from reliable sources. Additionally, the application incorporates a dog breed classifier utilizing CNNs, particularly the ResNet50 architecture, as an added feature. This classifier enhances the user experience by allowing the identification of dog breeds from images, providing users with instant breed information. The development process includes data collection, curation, and preprocessing of diverse dog breed datasets. Machine learning models are trained, optimized, and integrated into the application interface to ensure seamless functionality. The significance of this project lies in its contributions to the dog breeding community, offering a user-friendly platform that assists breeders and enthusiasts in making well-informed decisions regarding dog breed selection and breeding practices.

Contents

List of Abbreviations

CNN - Convolutional Neural Networks

AI - Artificial Intelligence

NASNet - Neural Search Architecture Net

KNN - K-Nearest Neighbor

MAE - Mean Absolute Error

MSE - Mean Squared Error

RMSE - Root-Mean-Square Error

R-CNN - Region-Based Convolutional Neural Network

DDCF - Decay Collaborative Filtering

CF - Collaborative Filtering

AP - Average Precision

AKNN - Adaptive K-Nearest Neighbors

ReLU - Rectified Linear Unit

SQL - Structured Query Language

List of Figures

Chapter 1

Introduction

1.1 Background

The world of dog breeding and ownership encompasses a diverse array of breeds, each exhibiting unique characteristics, temperaments, and care needs. This diversity poses a challenge for dog enthusiasts, breeders, and potential dog owners seeking guidance in selecting suitable breeds that align with their preferences and lifestyle. Currently, the process of identifying an ideal dog breed involves extensive research across various sources, including breed-specific websites, books, and consultation with breeders or veterinarians. While these resources offer valuable insights, the sheer volume of available information often leads to confusion and decision-making challenges for individuals looking to adopt or breed dogs. The emergence of technology-driven solutions has reshaped numerous facets of our lives, including pet care and companion selection. Recognizing this opportunity, the development of a specialized dog breeding application aims to address the inherent complexities in breed selection and profiling. The proposed dog breeding application stands as an innovative solution tailored to streamline and simplify the breed selection process. It caters to the needs of diverse user groups, providing comprehensive breed profiling, recommendation services, and advanced breed identification features through image classification.[1].

1.1.1 Importance of the Project

The proposed dog breeding application stands as an innovative solution tailored to streamline and simplify the breed selection process. It caters to the needs of diverse user groups, providing comprehensive breed profiling, recommendation services, and advanced breed identification features through image classification.

Key factors contributing to the significance of this project include:

- Enhanced User Experience: The application aims to provide a user-friendly interface, offering an intuitive platform for users to input their preferences and receive personalized breed recommendations.

- Accurate Breed Profiling: By leveraging historical breed data and advanced machine learning algorithms, the application ensures the delivery of accurate and detailed breed profiles, encompassing temperament, activity level, grooming requirements, and more.

- Efficiency and Accessibility: With a vast database of dog breeds and streamlined recommendation processes, the application offers efficiency in decision-making, empowering users to access reliable information at their fingertips.

- Educational Resource: Beyond serving as a selection tool, the application serves as an educational resource, fostering awareness and knowledge about various dog breeds, their origins, and unique attributes.

1.2 Problem Definition

The primary objective of this project is to develop an intelligent dog breeding application equipped with a breed recommendation system and a robust breed classification feature. This application aims to simplify the process of selecting an ideal dog breed for potential owners or breeders while offering accurate and comprehensive information about various dog breeds.

1.3 Scope and Motivation

The scope of this project revolves around creating an all-encompassing dog breeding application that merges breed classification technology with a recommendation system. The application will utilize machine learning models, particularly image classification algorithms, to accurately identify and classify dog breeds from images. Additionally, it will offer detailed profiles of different dog breeds, encompassing characteristics, temperament, care requirements, and suitability for various living conditions. The application's recommendation system will leverage user preferences, living conditions, and other specific criteria to suggest suitable dog breeds, ensuring a tailored and user-friendly experience for potential dog owners or enthusiasts.

The motivation behind this project stems from the increasing interest in dog ownership and the challenges individuals face when choosing an appropriate dog breed. Providing an easily accessible and reliable platform that offers comprehensive information on dog breeds and assists in selecting the most compatible breed for an individual's lifestyle is the core motivation. This project aims to simplify and streamline the dog breed selection process, addressing the concerns of both prospective dog owners seeking guidance and breeders aiming to match dogs with suitable owners. The fusion of technology and dog breeding expertise will cater to the growing demand for accurate information and personalized guidance in the domain of dog breeding and ownership.

1.4 Objectives

- Develop an efficient dog breed classification model leveraging machine learning algorithms to accurately identify various dog breeds from images.
- Implement a user-friendly interface for the dog breeding application, allowing users to input preferences and criteria for personalized breed recommendations.
- Create a comprehensive database containing detailed profiles of different dog breeds, encompassing attributes like temperament, exercise needs, grooming requirements, and health considerations.
- Integrate the recommendation system with the breed classification model to suggest suitable dog breeds based on user inputs, considering lifestyle, living conditions, and preferences.
- Conduct thorough testing and validation of the classification and recommendation algorithms to ensure accuracy, reliability, and consistency in breed suggestions.

1.5 Challenges

- Data Collection and Quality: Acquiring a diverse and comprehensive dataset of high-quality dog images representing various breeds might pose a challenge.
- Algorithm Accuracy: Ensuring the accuracy and reliability of the breed classification and recommendation algorithms while considering the complexities of dog breeds and individual variations.
- User Preferences: Addressing the intricacies of user preferences and lifestyle factors to provide accurate and personalized dog breed recommendations.
- Model Complexity and Computational Requirements: Dealing with the complexities of deep learning models for image classification, which might require substantial computational resources and longer training times.

1.6 Assumptions

- Standardized Breed Identification: Assuming the availability of standardized breed labels for the dog images in the dataset.
- Uniform Image Quality: Assuming a level of consistency in image quality and clarity across the dataset to facilitate accurate classification.
- Reliable User Input: Assuming the reliability and accuracy of user-provided preferences and information for generating suitable dog breed recommendations.
- Sufficient Training Data: Assuming the availability of a sufficient amount of diverse and labeled dog images for training the classification model effectively.

1.7 Societal Relevance

The dog breed classification system envisioned in this project has multifaceted applications across different domains, benefiting both society and industry. Foremost, it plays a pivotal role in veterinary care and diagnosis by assisting veterinarians in swiftly identifying dog breeds. This aids in offering breed-specific medical care, understanding prevalent health issues associated with particular breeds, and facilitating appropriate treatment methods. In the context of animal shelters and adoption centers, the system streamlines the process of matching dogs with potential owners. By swiftly recognizing dog breeds and their unique characteristics, shelters can efficiently pair dogs with individuals or families based on lifestyle compatibility and preferences, thereby enhancing the prospects of successful and lasting adoptions. Moreover, the project significantly contributes to dog training and behavioral analysis. It enables trainers to gain insights into breed-specific behaviors and tendencies, empowering them to tailor training programs that resonate with specific breeds. This targeted approach facilitates more effective training, resulting in well-behaved and trained dogs. For breed enthusiasts and prospective pet owners, this classification system serves as an invaluable resource. It offers comprehensive insights into breed characteristics, enabling individuals to make informed decisions when selecting a dog breed that aligns with their preferences, living conditions, and lifestyle. Furthermore, the system finds application in dog shows and competitions, providing judges and participants with a reliable tool to verify and authenticate dog breeds during competitions. This ensures compliance with breed standards, contributing to fair assessments and competitions. Overall, the project's broad applications cater to stakeholders involved in dog care, welfare, ownership, and breeding, fostering informed decision-making and improved animal welfare standards.

1.8 Organization of the Report

The CanineMate project report is systematically structured to provide a comprehensive understanding of the proposed Dog Breeding Application with Breed Profiling and Recommendation System. Chapter 1 establishes the project's foundation, emphasizing its significance, defining problems, outlining scope and motivation, and setting clear objectives. Challenges and potential issues are acknowledged, assumptions are disclosed, and the social relevance of the project is highlighted. This chapter serves as a crucial introduction, paving the way for a deeper exploration of the project in subsequent chapters. In Chapter 2, a literature survey delves into insights from foundational and reference papers, establishing a robust theoretical foundation. Chapter 3 addresses hardware and software requirements, providing clarity on the technical infrastructure. Chapter 4 encompasses the system architecture, offering a holistic view with diagrams and a module-wise division. The work breakdown and schedule ensure effective project management. Finally, Chapter 5 concludes the report, summarizing key findings, achievements, and potential enhancements, maintaining an organized flow from conceptualization to insights.

Chapter 2

Literature Survey

2.1 Related Works

This section provides a detailed discussion of the overviews of current methods for physical image categorization and recommendation systems. By leveraging the learning features and weights of ResNet50 through transfer learning,[2] demonstrated improved categorization of dog breeds. Compared to training from scratch, transfer learning with ResNet50 yielded superior results, highlighting its efficacy in enhancing model accuracy for dog breed identification tasks. In [3] ResNet50 served as the primary network for feature extraction in cat class recognition and segmentation.Its ability to capture intricate patterns and hierarchical features contributed to improved recognition and segmentation of cat classes, showcasing the utility of ResNet50 in deep learning tasks involving cat imagery.The paper [4] shows how ResNet50 addressed challenges such as the vanishing gradient issue and data constraints, thereby improving the model's capability to accurately identify and categorize cat breeds in the mobile application setting

Exploring the significance of similarity metrics in recommender systems, [5] focused on collaborative filtering and its impact on recommendation accuracy. Various metrics such as Pearson correlation, Euclidean distance, Cosine similarity, and Jaccard coefficient were discussed in the context of user-based suggestion evaluation. The study underscored the importance of selecting appropriate similarity measures based on dataset properties to optimize recommendation accuracy and algorithm selection for effective collaborative filtering deployment. Many studies have been done in the field of movie recommendation systems to improve user experience and offer precise recommendations, concentrated on grouping items according to user similarities in order to increase the accuracy of recommender systems. This method sorts things according to the user's preferences. The user's previous ratings are used to determine the result.In [6] The Vector Space Model (VSM) is the method used to model this approach. The item's similarity is inferred from its description, and the notion of TF-IDF (Term Frequency-Inverse Document Frequency) is presented.

2.2 Literature Papers

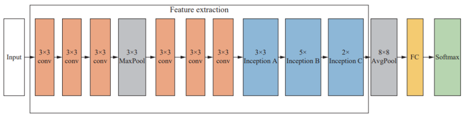
2.2.1 Identifying a Dog Breed with Deep Learning

The paper shows that dog breeds can be recognized from a dog facial image using deep learning, although there are still issues with increasing the classification accuracy.According to the study, dog breed categorization performed better when rotation and translation were used in training sets. The NASNet model had the highest accuracy. The study discovered that their approach produced the best accuracy when comparing its findings with those of earlier investigations.

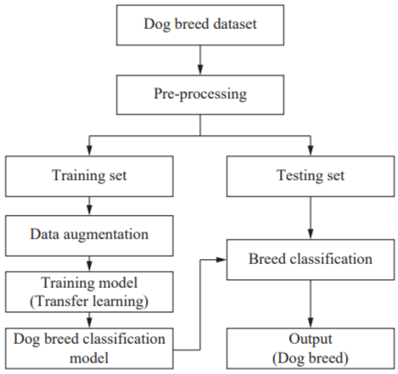
The method for distinguishing dog breeds from photos of their faces that uses deep learning is suggested in this study. To improve classification accuracy, the approach combines pre-trained convolutional neural networks (CNNs) with transfer learning techniques and augments picture input. Three CNN models—MobilenetV2, InceptionV3, and NASNet—that were trained on training sets that included image augmentation techniques like rotation, translation, and random noise are examined in this work. With rotation images from the training set, the NASNet model is trained, and it reaches the highest accuracy of 89.92%. Although the trials acknowledge the current obstacles to increasing classification accuracy, they also show how deep learning can be used to identify dog breeds from photos. The outcomes demonstrate how well the suggested strategy works to identify dog breeds with promising accuracy.

The proposed method for identifying dog breeds using deep learning, transfer learning, and image data augmentation can be identified based on the information provided in the paper.

Some of its advantages being. High Accuracy: The suggested method outperforms earlier approaches in recognizing dog breeds from photographs, achieving a high accuracy of 89.92Transfer Learning: By utilizing pre-trained convolutional neural networks (CNNs) for transfer learning, a greater amount of training data and processing resources can be avoided while still utilizing current models and knowledge. Image Data Aug-



(a) Inception V3 architecture. Conv represents convolutional layer, FC represent the fully connected layer. Colored figures are available in the online version.



(b) Overview of the proposed framework

Figure 2.1: Architecture

mentation: By applying techniques like rotation, translation, and random noise to image data, the model's robustness and generalization are improved, which improves classification accuracy. Possibility for Additional Research: By employing pre-trained models with fine-tuning, the outcomes of the suggested method can provide a solid foundation for upcoming studies on dog identification and offer insightful knowledge on the distinguishing characteristics of different dog breeds.

Some of its disadvantages being. Limited Evaluation: The study does not go into great detail about the drawbacks or difficulties that can arise with the suggested approach, such as how different image characteristics, occlusions, or environmental factors might affect the accuracy of classification. Computational Complexity: Although transfer learning can lessen computational complexity, deep learning model training and fine-tuning—especially with large datasets—may still call for a substantial investment of time and processing power. Interpretability: Deep learning models, especially those that use transfer learning, might not be able to be understood in terms of the precise traits or qualities that are used to classify dog breeds. This could limit our ability to grasp how the model makes decisions.

Overall, the suggested approach—which makes use of transfer learning and image data augmentation—performs admirably in terms of recognizing dog breeds from photographs. To address potential drawbacks and difficulties related to computational complexity and model interpretability, more study is necessary.[1]

2.2.2 Movie Recommender System Using K-Nearest Neighbors Variants

The use of K-Nearest Neighbors (KNN) techniques for creating Movie Recommender Systems with the MovieLens dataset is the main topic of both the paper and the article. They present various KNN algorithm iterations with a range of similarity criteria and assess their effectiveness on actual data using accuracy metrics. The related work, the recommender system architecture, and the KNN algorithm variants are all included in the paper. Additionally, it displays the experiment outcomes and makes inferences from the data. Conversely, the paper assesses the accuracy of several KNN algorithms by comparing their performance with different similarity measures and using metrics as FCP, MAE, MSE, RMSE, Precision@k, and Recall@k.

It concludes that the suggested KNN algorithms function well with the MovieLens dataset and makes recommendations for possible advancements for next research. The significance of assessing recommendation systems and algorithms for movie recommendations is emphasized in both the paper and the article. They compare the performance of various KNN algorithms and their variants using actual data from the MovieLens dataset. Accuracy measures like FCP, MAE, MSE, RMSE, Precision@k, and Recall@k form the basis of the evaluation. The results indicate that the suggested KNN algorithms perform well on the MovieLens dataset, suggesting that movie recommendation systems may find use for them. The report also highlights the continuing nature of research in this sector by identifying areas for future development.

The article and paper offer insightful information about the application of KNN algorithms to movie recommendation. Using actual data from the MovieLens dataset, they provide a thorough review of the effectiveness of several KNN algorithm modifications with various similarity measures. The results point to the algorithms' potential for precise movie suggestions and offer directions for future study and development of recommendation systems.

When creating a movie recommender system, options for the K-nearest neighbors (KNN) algorithm with varying similarity metrics enable for flexibility and customisation. This method may result in more accurate and effective movie recommendations for users. The MovieLens dataset's real data is used to evaluate the KNN algorithms, offering useful insights into how well they perform in actual situations. The suggested algorithms'

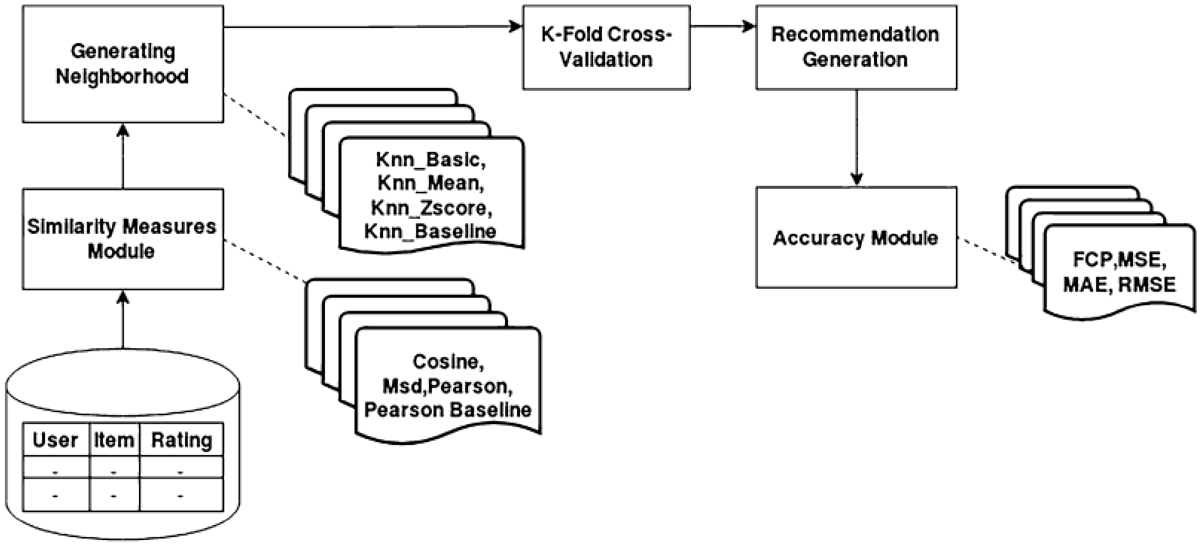


Figure 2.2: Proposed architecture for movie recommender system

legitimacy and likelihood of being used in real-world situations are strengthened by this empirical validation. An extensive analysis of KNN algorithms' performance is provided by contrasting them and their variants and evaluating them using multiple accuracy metrics. This can assist in determining the best algorithm for suggestions of movies depending on particular needs and performance standards.

It's possible that the paper and article don't offer a thorough comparison with alternative recommendation algorithm kinds like collaborative filtering or deep learning techniques. This restricts our ability to comprehend how KNN algorithms compare to other techniques for suggesting movies. The MovieLens dataset, on which the KNN algorithms are evaluated, may not accurately capture the complexity and variety of actual movie recommendation scenarios. There may be restrictions on how broadly the results can be applied to other datasets or recommendation systems. To get ideal performance, the suggested KNN algorithms and its variants can need a great deal of parameter tuning and optimization, which can be resource- and time-intensive. When putting the recommender system into practice and deploying it, this factor should be taken into account.[7]

2.2.3 Animal Species detection and classification

- YOLOv3 : YOLOv3 is a single-stage object detection algorithm known for its speed and accuracy. It was presented as a benchmark for comparison, demonstrating its efficiency in detecting multiple animal species across various datasets. The study highlighted YOLOv3's performance in comparison to other architectures, showcasing its advantages and limitations concerning accuracy and speed

- R-CNN Variants : Different variants of R-CNN were explored. Cascaded R-CNN, Faster R-CNN, and RetinaNet were evaluated for their ability to accurately detect and classify animals in images. The literature discussed the intricacies of these architectures, focusing on their underlying mechanisms like region proposals, anchorbased strategies, and feature pyramid networks.

- Comparative Analysis: The literature provided a comparative analysis of these architectures, delineating their respective strengths and weaknesses. It highlighted performance variations concerning metrics such as Average Precision (AP) across different animal classes in distinct datasets. For instance, it showcased where YOLOv3 outperformed other models or where R-CNN variants excelled in precision.

- Attention Mechanisms: The text briefly touched upon attention mechanisms incorporated within some models, describing their potential enhancement in the recognition and classification of animals. It outlined how these mechanisms aid in focusing on relevant image regions and improving model accuracy.[8]

2.2.4 A collaborative filtering recommendation system with dynamic time decay

A novel approach to collaborative filtering (CF) recommendation systems, called Dynamic Decay Collaborative Filtering (DDCF) is proposed here. The authors address the challenges of data sparsity and changing user preferences over time by incorporating the concept of dynamic decay functions and item clustering. It addresses the challenges of traditional CF methods, which often struggle with data sparsity and changing user preferences. The proposed DDCF can be taken as a solution to these challenges, incorporating the concept of dynamic decay functions to capture changing user preferences over time. The concept of item clustering is also introduced here, which groups similar items without predefined parameters, effectively addressing the cold start and sparsity issues.

The paper presents the DDCF algorithm, which consists of four steps: item clustering, interest level identification, decay function specification, and preference prediction.

The initial part of the DDCF algorithm is to group similar items together without given parameters in advance. The K-means clustering algorithm is employed to cluster items based on their similarity. This is an important step in solving the cold start and sparsity problems of recommendation systems. The second step is to identify the interest level of each cluster based on the time and number of rating records in the cluster. The idea of human brain memory to specify the level of a user's interests is extended here, i.e., instantaneous, short-term, or long-term. The third step is specify a decay function for each interest level. Four types of decay functions are proposed: linear, exponential, power, and logistic. The limitations of previous studies that used only one decay function to model changes in user preferences are also explained, pointing out the importance of adopting multiple decay functions according to the number and time of item ratings. The prediction of users' preferences based on the determined interest level and decay function is done in the last step. DDCF uses baseline estimation together with decay, item-based recommendation to estimate users' ratings.

Experiments are conducted on real datasets, including MovieLens-100K and MovieLens-1M, to evaluate the performance of DDCF. The results of DDCF are compared with other recommendation algorithms, including item-based collaborative filtering (IBCF), and decay collaborative filtering (DCF) with different decay functions. The experimental results indicate that DDCF outperforms other algorithms in terms of F-measure, particularly with top-N recommendations. DDCF achieves high F-measure values for top-10 and top-50 recommendations, showcasing its effectiveness in providing accurate and relevant recommendations to users.

The limitations are also discussed here, including the need for further research to evaluate the effectiveness of DDCF on larger datasets and the need to explore other decay functions. It concludes by summarizing the findings and contributions of the proposed DDCF system, emphasizing its effectiveness in addressing the challenges of data sparsity and changing user preferences in collaborative filtering-based recommendation systems.

So to summarize, the paper presents a pioneering approach to collaborative filtering recommendation systems, addressing the limitations of traditional methods by incorporating dynamic decay functions and item clustering to capture changing user preferences over time and mitigate data sparsity issues. The experimental results demonstrate the superior performance of DDCF in providing accurate and relevant recommendations, making it a promising advancement in the field of recommendation systems. The authors provide a comprehensive review of related work, a detailed explanation of the DDCF algorithm, and a thorough evaluation of its performance on real datasets, highlighting its effectiveness in addressing the challenges of data sparsity and changing user preferences.[9]

2.2.5 Adaptive KNN-Based Extended Collaborative Filtering Recommendation Services

An adaptive KNN-based extended collaborative filtering model, is proposed in this paper for use in recommendation systems. The model incorporates user cognition factors and dynamically updates user clusters in an attempt to overcome the drawbacks of conventional collaborative filtering techniques. The suggested model performs better than benchmark models in terms of accuracy measures, according to experimental results.

The suggested model makes use of Adaptive K-Nearest Neighbors (AKNN), a better KNN algorithm with user configurable settings. To generate a list of top-N recommendations, it dynamically modifies the value of K based on the sparsity of the data and takes user cognition into account. Using the MovieLens datasets, the model's performance is compared to various baseline approaches, demonstrating the model's greater accuracy and suggestion relevance.

Assessment measures including MAE, RMSE, MAP, and NDCG are used to compare the model to other benchmarks and show that it performs better than other approaches in terms of prediction accuracy and suggestion quality. The assessment of the model is conducted on the MovieLens dataset. Even for first-time users or those with little knowledge, the model works well at producing tailored recommendations. Future research will examine the model's execution time performance and extend it to cross-domain recommendation.

Additionally, The section also includes a list of references on recommender systems and collaborative filtering, including several topics like feature extraction, adaptive KNN, nearest neighbor classifiers, ensembling local learners, social recommender systems, hybrid recommender systems, and predictive models for collaborative filtering. Studies on the Movielens dataset, the impact of perceived utility on purchase intention, attention-based user modeling, and knowledge-driven digital nudging techniques are among the other references. We explore several collaborative filtering algorithms and similarity measures, including contextual collaborative filtering, SVD, item-item collaborative filtering, co-clustering, and TF-IDF.

Some of the advantages of this proposed model are the following. Increased Recommendation Accuracy: the model performs better in terms of accuracy measures than benchmark models, demonstrating its capacity to produce tailored and pertinent suggestions. User Cognition Incorporation: The model overcomes the drawbacks of conventional collaborative filtering algorithms by including user cognition characteristics, which improve the relevance and personalization of recommendations. Some of its disadvantages being.Computational Complexity: Adding user cognition parameters and dynamically adjusting K's value based on data sparsity could result in more computational complexity, which could affect processing times and resource needs. Dependency on User Cognition Parameters: Depending on the availability and quality of user cognition parameters, which may differ between user groups or domains, the model's applicability may be limited.[10]

2.2.6 Deep viewing for the identification of Covid-19 infection status from chest X-Ray image using CNN based architecture

Convolutional Neural Networks (CNN) are used in this research study to automatically diagnose Covid-19 from chest x-ray pictures. High F1-score, sensitivity, specificity, accuracy, and precision were attained by the suggested CNN architecture in differentiating between pneumonia cases and Covid-19 patients. The study highlights the potential advantages of the CNN model for academics and physicians, emphasizing how crucial it is to identify Covid-19-related pneumonia quickly and accurately[11]. The study also addresses the shortcomings of the testing procedures used today and the necessity of larger datasets and radiologists' cooperation in future research. Additionally, it offers a selection of research publications that highlight the developments in this field of study and concentrate on the identification of COVID-19 utilizing deep learning methods and medical imaging data.

The three stages of the authors' approach include pre-processing, CNN model training, and performance evaluation. Multiple convolutional blocks with ReLU activation functions, dropout layers, and fully linked layers make up the suggested CNN model. Covid-19, pneumonia, and normal case x-ray pictures are included in the training and testing dataset. The significance of timely and precise identification of Covid-19-associated pneumonia, as well as the shortcomings of existing diagnostic techniques, are also covered by the writers. They draw attention to how quickly and accurately x-ray scans can be used to identify suspected Covid-19 cases. The goal of the suggested methodology is to help radiologists and medical professionals recognize x-ray abnormalities and differentiate between normal instances, pneumonia, and Covid-19.

Convolution layers with ReLU activation function, zero padding layer, pooling layers, dropout layer, fully connected layer, and softmax function are all included in the proposed CNN architecture for Covid-19 detection. Unbalanced data is handled via cost-sensitive learning. The model classified Covid-19, normal, and pneumonia patients with high accuracy, specificity, sensitivity, precision, and F1-score. It did a good job of separating Covid-19 cases from pneumonia cases as well. When the outcomes were compared to other architectures, they demonstrated strong performance.

Based on chest x-ray pictures, the authors created a deep learning model with CNN to categorize people with Covid-19, pneumonia, and healthy persons. They attained high accuracy and performance metrics by comparing the performance of their model with other deep learning models. Additionally, they ran a 5-fold cross-validation to confirm the model's resilience. The outcomes demonstrated how well their algorithm can distinguish between Covid-19 patients with pneumonia and healthy people. The suggested model performed better at detecting Covid-19 than other cutting-edge models.[11]

Chapter 3

Requirements

3.1 Hardware Requirements

- 8GB RAM
- Intel i5-10210U CPU 10th gen
- 1.60GHz 2.11 GHz
- SD with at least 2 GB storage
- Intel UHD integrated graphics

3.2 Software Requirements

- VS code
- Python: 3.8.5 (or 3.x)
- Tensorflow: 2.3.1
- Opencv: 4.1.2
- Sklearn: 0.24.2
- Numpy: 1.19.5
- Pandas: 1.1.5
- Matplotlib : 3.2.2

Chapter 4

System Architecture

4.1 System Overview

The proposed model for the comprehensive dog breeding application involves a multi-faceted architecture that integrates several modules. Firstly, the system consists of an intuitive and user-friendly interface allowing users to input data and preferences. This input is then meticulously processed and stored, encompassing various aspects such as dog images, breed-specific information, behavioral traits, health records, and user preferences.

Central to the model is the utilization of Convolutional Neural Networks (CNNs) trained on pre-existing models like ResNet, Inception, or EfficientNet for robust and accurate dog breed classification. These CNNs are adept at understanding complex image patterns and can accurately classify dog breeds from images, offering a detailed and precise identification.

Moreover, the system incorporates a recommendation system that compares user profile elements based on cosine similarity. By calculating the cosine similarity of user vectors, the algorithm finds profiles that are comparable. This makes it possible to create unique suggestions based on the weighted ratings of users who are mostly similar to each other.

Our approach makes use of compatibility scores that are obtained from multiple aspects, such as breed traits and health considerations, to enhance user satisfaction and enhance the welfare of future dog generations.

All these components are seamlessly interconnected and orchestrated through a web based interface, offering a unified and accessible platform for users. Rigorous evaluation, testing, and refinement of the model are imperative to ensure its accuracy, reliability, and user satisfaction, making it a comprehensive and valuable tool for individuals seeking guidance in choosing a suitable dog breed based on their preferences and lifestyle.

4.2 Architectural Design

4.2.1 Architecture Diagram

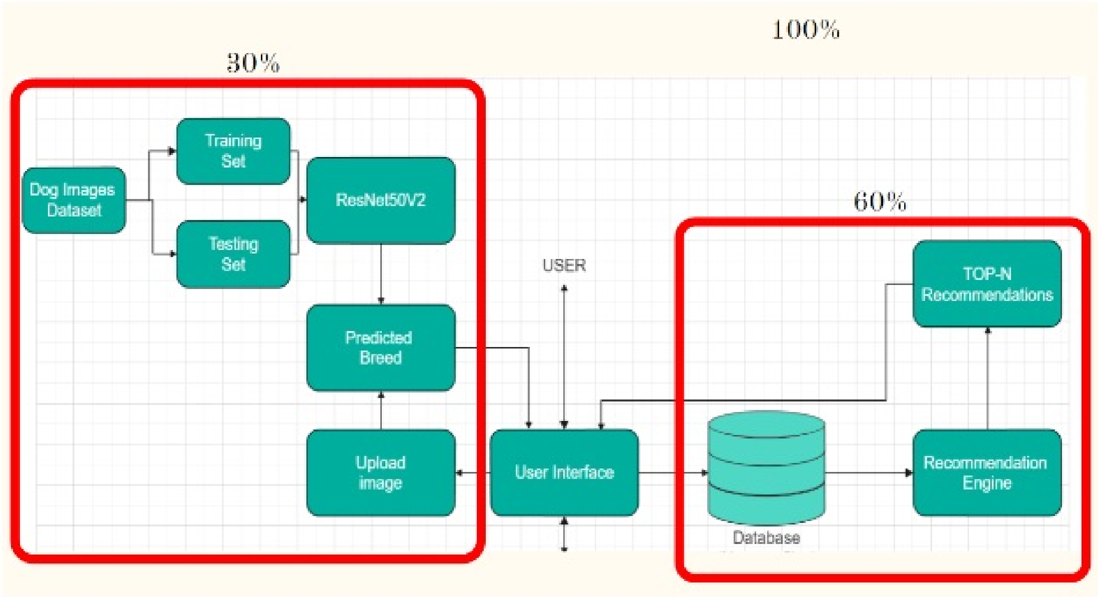


Figure 4.1: Architectural Diagram

4.2.2 Sequence Diagram

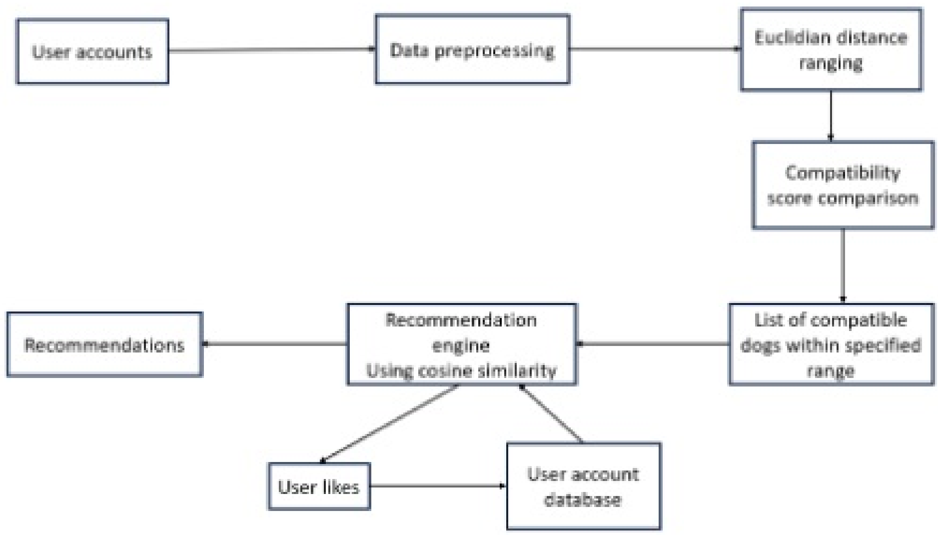


Figure 4.2: Sequence Diagram

4.3 Module Division

4.3.1 Dog breed classification module

Convolutional, pooling, activation, and fully-connected layers are layered one on top of the other in ResNet. Convolutional networks function by multiplying pixel values by weights and then adding them together to aid in the classification of complicated images. Edge detection may be taught to the first layer. Perhaps the second layer will pick up texture recognition. Object detection can be taught to the third layer. The ImageNet database contains over a million photos that have been pre-trained for these layers of ResNet. ResNet's multiple layers help it address complicated issues and improve the performance and accuracy of the model. Each ResNet starts with a 3x3 or 7x7 initial filter or kernel with a stride of 2. Resnet50V2 (version 2), which is 50 layers deep and applies Batch Normalisation and RELU activation function before to the input being multiplied by convolutional operations (weight matrix), will be used in this research.

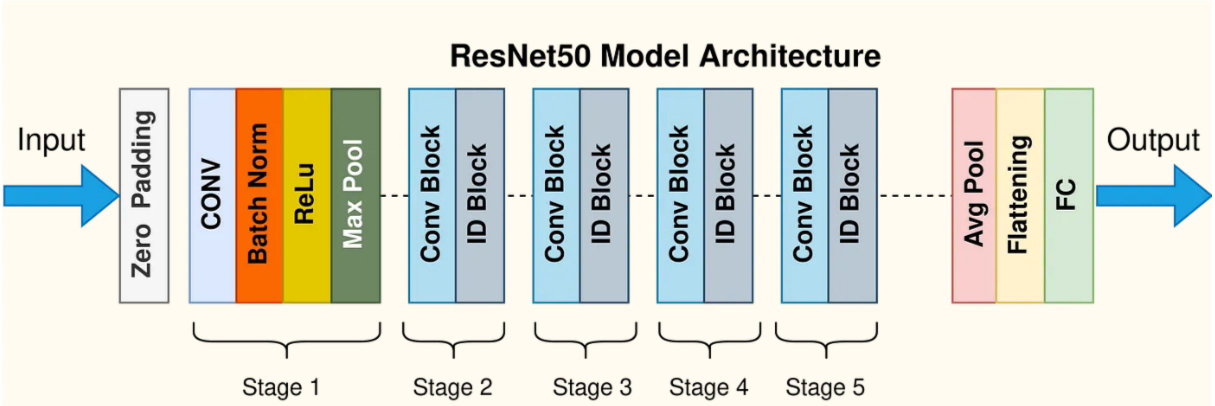


Figure 4.3: ResNet Model Architecture

4.3.2 Recommendation system module

The recommended dog breed suggestion engine compares user profile elements based on cosine similarity. By calculating the cosine similarity of user vectors, the algorithm finds profiles that are comparable. This makes it possible to create unique suggestions based on the weighted ratings of users who are most like each other.

Here is a detailed description of each step of the app:

Initially, each canine profile's features are kept in a database. Breed, Gender, Age, Height, Weight, Expectancy, Group, shedding value, shedding category, energy level value, energy level category, trainability value, trainability category, demeanour value, and demeanour are some of these qualities. When a person opens an account, they can access these features.

Using content-based filtering, we suggest alternative dog profiles once users have entered all these details. Recommendations are based on the accounts that the user has already shown interest in. After a user likes another account, we suggest users who are similar to the liked user using a content-based recommendation engine that employs cosine similarity.

The content-based filtering's primary flaw is its cold start issue. We used a different database to provide an initial recommendation in order to address this. This database was constructed with each dog's compatibility score in mind.

A compatibility score is a figure between 1 and 10. The compatibility score indicates how well one dog should be bred to another in order to produce the healthiest offspring and to select a dog to breed in which the parents' post-breeding health is good. These sores are from a dataset that was produced by taking into account all the variables and using information from organisations such as the Kernal Club of America and India.

Each user's location information is gathered, and the compatibility score is taken into account when making the first recommendations so that users will find them appealing and allow for the creation of more. The user specifies a range, after which the other users are filtered by the range and the Euclidian distance between the user and other users is computed. Following the acquisition of these filtered people, the compatibility score is used to rank the list in decreasing order.

The purpose of this list is to get the user to enjoy it at the beginning. When a person likes a profile, the likes are saved in a database that is designated for that user alone; each user's database is distinct yet identical.

The recommendation algorithm receives its input from this user-specific database. Cosine similarity is used to compare the records in the user-specific database with the database containing all of the user's information. The users see the matches that have the most resemblance.

This is done in order to provide the user with recommendations for profiles that meet their likes and preferences and to provide them with the recommendations that are most compatible with producing healthier puppies and lowering the dangers to the parents' health.

4.4 Work Breakdown

- Alex Santhosh: Classification model
- Alen Theethai Babu(Lead):Recommendation system(Python)
- Amal Stephen: Front-end ,flask connections
- Alan Baby George: Database Manipulation(SQL).

4.5 Work Schedule - Gantt Chart

Figure 4.4: Gantt Chart

Chapter 5

Result and Discussion

In conclusion, our research offers a thorough approach to dog breed classification and customized recommendations, backed by dependable technological elements and an intuitive online interface. During breed classification trials, the ResNet50v2 model demonstrated its ability to accurately identify dog breeds from user-submitted photos, with an accuracy of 80 percent and a loss of 0.2. In addition, our recommendation system makes use of cosine similarity scores as high as 0.99999 in order to offer customized recommendations based on individual user activities and interests on the site. The incorporation of an intuitive website interface augments accessibility by facilitating users' ability to interact with the platform's functionalities and obtain recommendations with ease.The results that we obtained are shown below.

```
64/64 [============================] - 58s 898ms/step - loss: 0.6798 - accuracy: 0.7937 - val_loss: 0.7465 - val_accuracy: 0.8037
Epoch 18/20
64/64 [============================] - 58s 897ms/step - loss: 0.6778 - accuracy: 0.7961 - val_loss: 0.7468 - val_accuracy: 0.7920
Epoch 19/20
64/64 [============================] - 57s 888ms/step - loss: 0.7084 - accuracy: 0.7888 - val_loss: 0.7390 - val_accuracy: 0.7979
Epoch 20/20
64/64 [============================] - 57s 894ms/step - loss: 0.6405 - accuracy: 0.8050 - val_loss: 0.7505 - val_accuracy: 0.7920
```

Figure 5.1: Accuracy readings

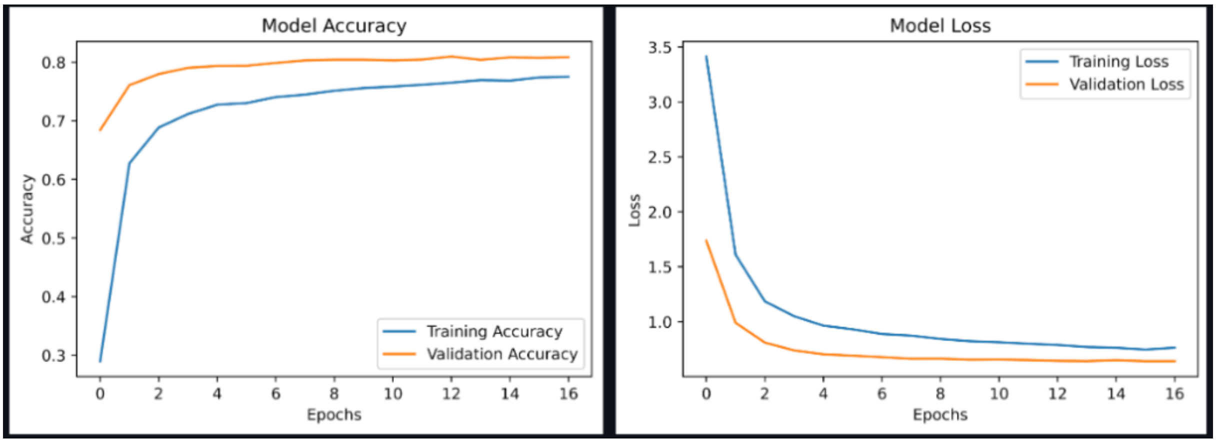


Figure 5.2: ROC curve obtained

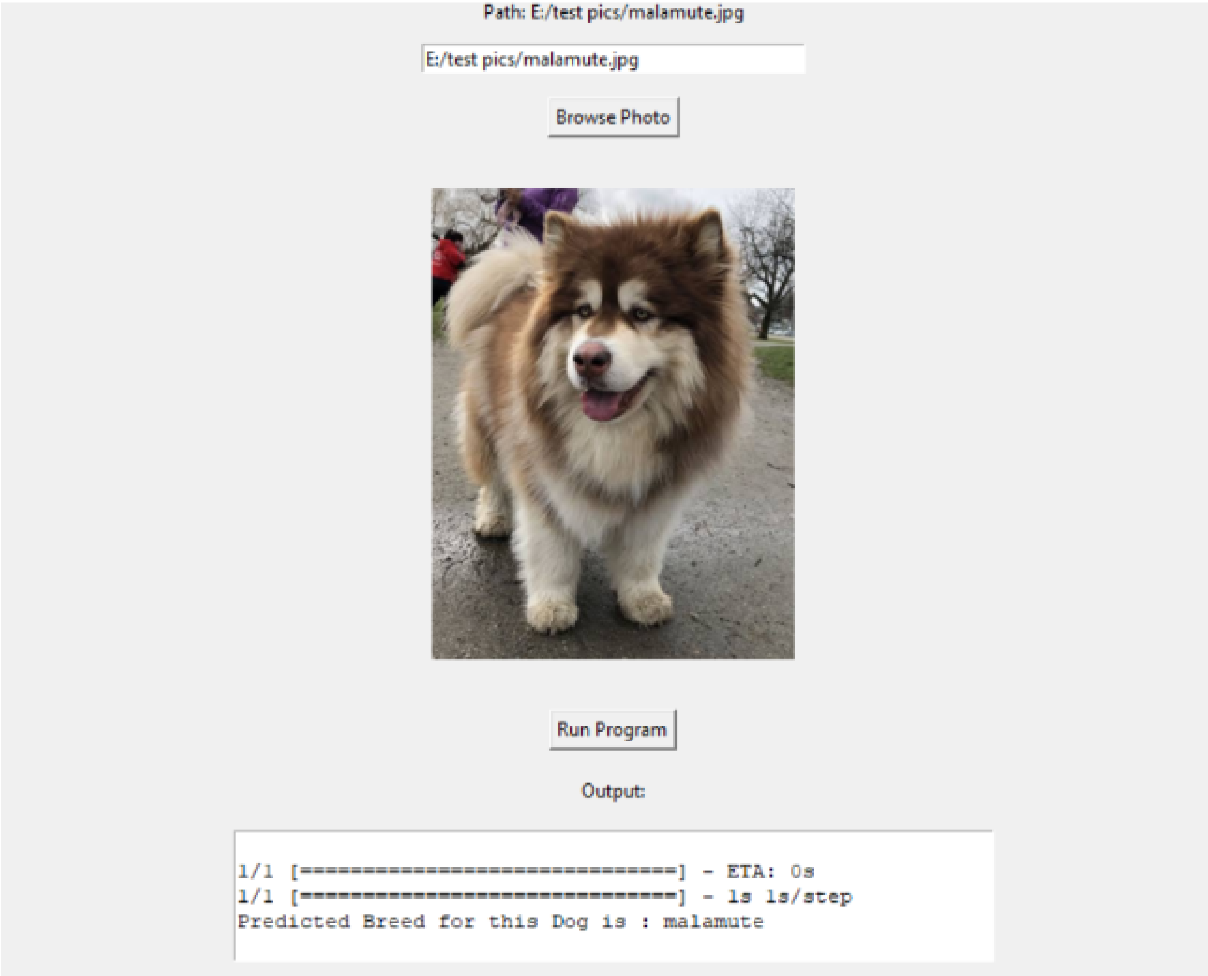


Figure 5.3: Classification model output

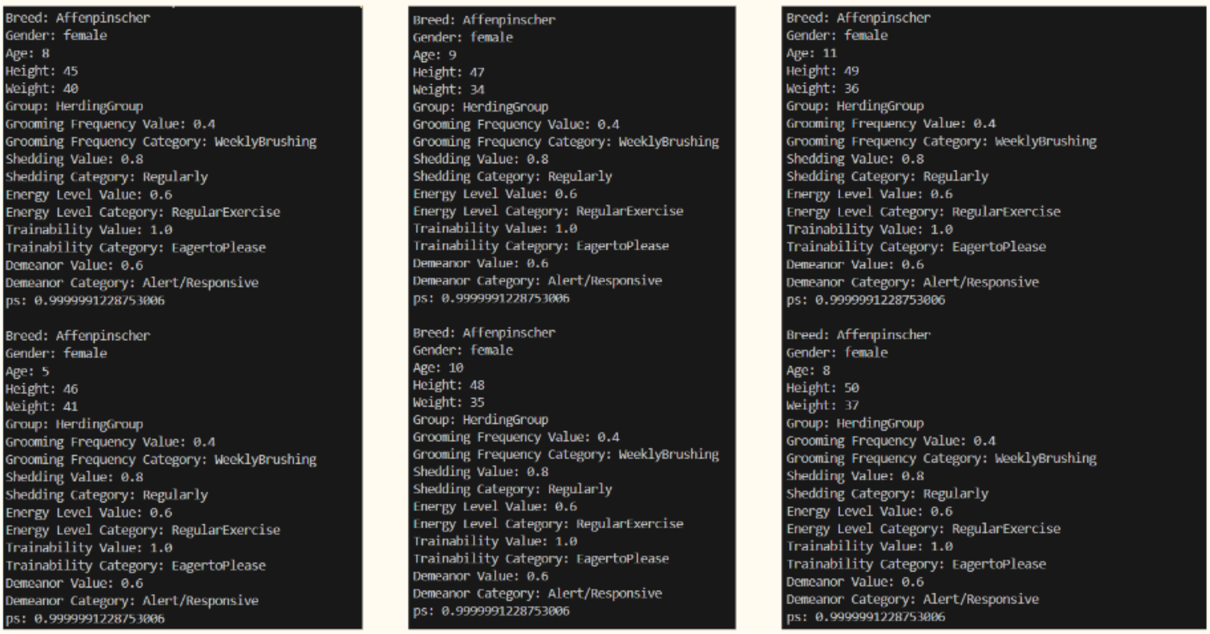


Figure 5.4: Recommended profiles based on cosine similarity

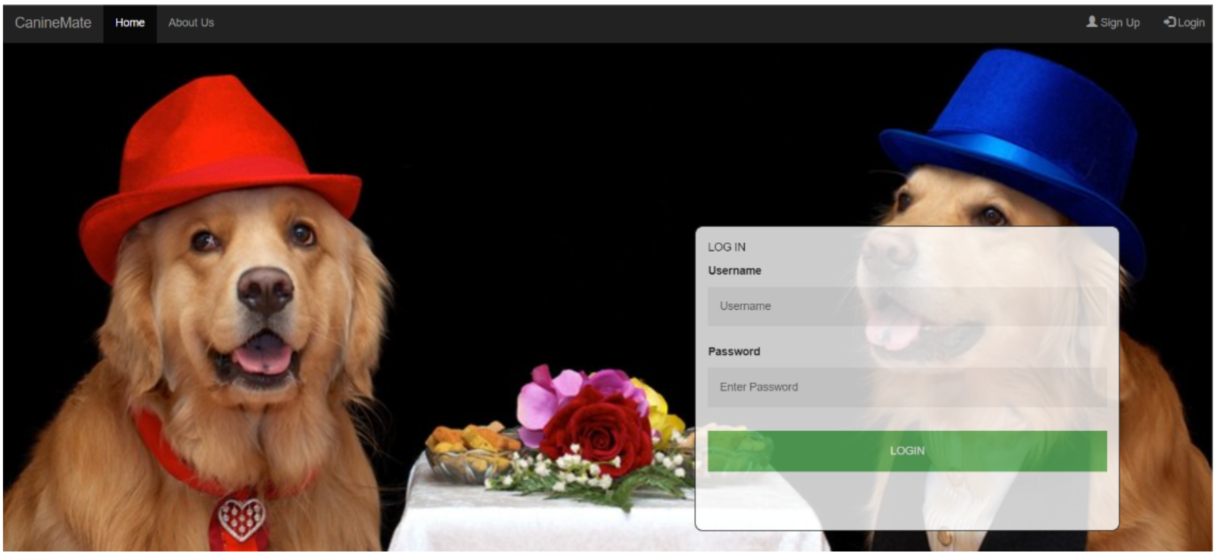


Figure 5.5: User login page

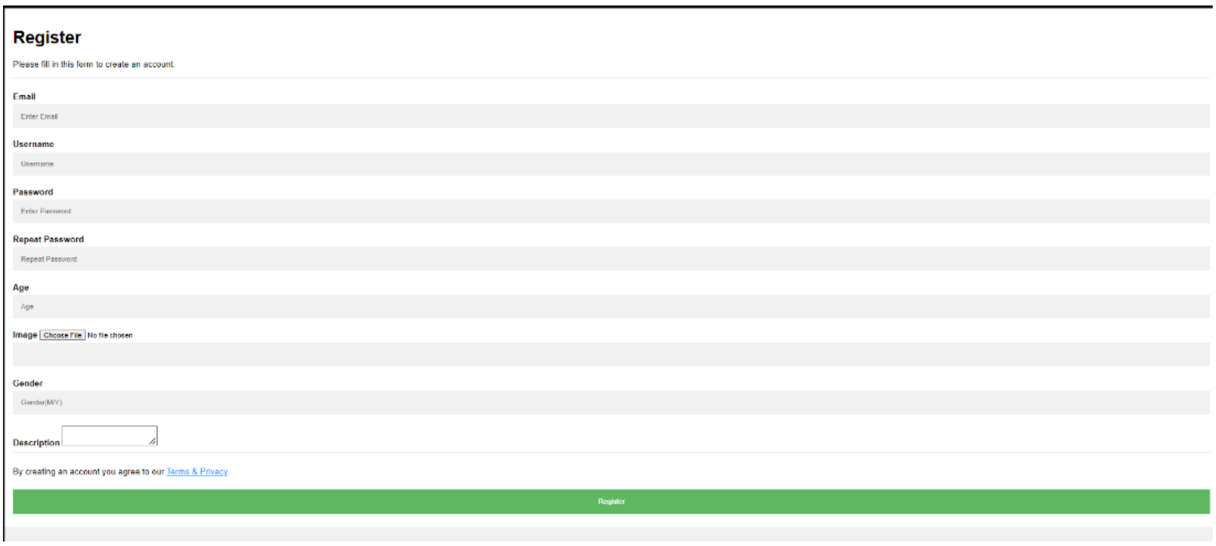


Figure 5.6: User registration page

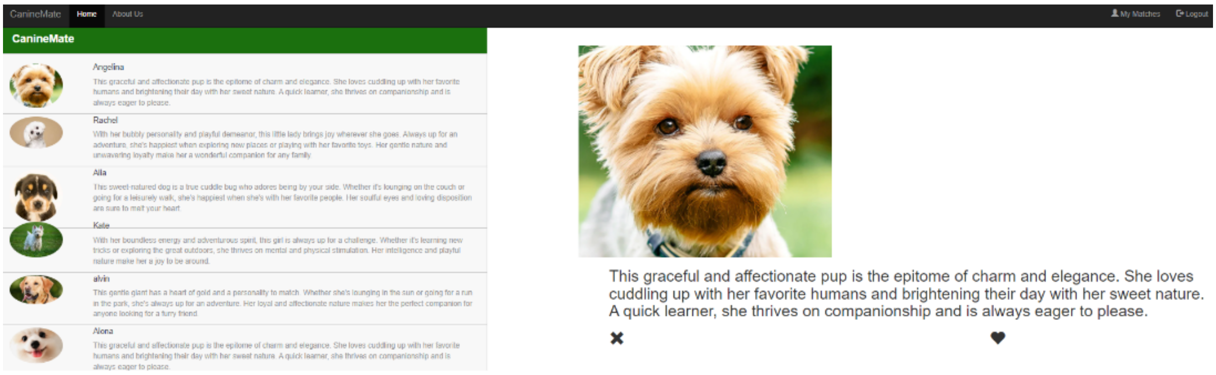


Figure 5.7: Home page

Chapter 6

Conclusion

Our project is a major advancement in the field of personalized recommendation systems and dog breed classification. We have created a strong platform that can reliably identify dog breeds from user-submitted photos and offer customized suggestions based on user preferences and previous interactions by utilizing machine learning and data-driven techniques. By incorporating compatibility scores and thorough dog profiles, we are able to solve cold start issues and encourage ethical dog breeding practices, both of which improve the health and well-being of our furry friends.

There is a great deal of room for improvement in this subject going forward. Additional data sources, such genetic information and behavioral features, may be incorporated into future iterations of our system to improve user experience and further refine recommendations. Additionally, working together with animal welfare groups and veterinarians could yield insightful information and guarantee that our platform always puts dogs' health and happiness first. Essentially, our initiative is a prime example of how technology may revolutionize the pet care industry. Utilizing state-of-the-art techniques and a thorough grasp of canine behavior and genetics, we have developed a tool that helps dog owners make decisions and builds a community committed to the welfare of our four legged friend.

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Appendix A: Presentation

PROJECT PRESENTATION

"Dog Breed Classification and Recommendation System Using ResNet50 and Cosine Similarity"

Group Members:
Alan Baby George
Alen T Babu
Alex Santhosh
Amal Stephen

Guide:
Ms. Jyotsna A

CONTENTS

PROBLEM DEFINITION

To create a centralized platform for responsible dog breeding using image classification and profile recommendation system to prioritize dog welfare, support responsible practices, and connect owners with healthy, suitable matches.

PROJECT OBJECTIVES

The primary objective of the "CanineMate" project is to establish an **online platform** that **facilitates responsible dog breeding and adoption** while prioritizing the **well-being** of dogs. Specifically, our goals are:

- To develop an app for promoting responsible dog breeding practices
- To verify the authenticity of the dog's breed using image processing.
- To recommend most suitable dog profile from given profiles.

NOVELTY OF IDEA

“CanineConnect" provides a centralized platform promoting responsible dog breeding. By promoting ethical practices and prioritizing dog welfare, it aims to foster a supportive community dedicated to responsible dog ownership.

Key aspects are:

- Image Classification
- Recommendation System

LITERATURE REVIEW

SL. NO	TITLE	AUTHOR	METHODOLOGY
1	Knowing Your Dog Breed: Identifying a Dog Breed with Deep Learning	Punyanuch Borwarnginn, Worapan Kusakunniran, Sarattha	Identification using Deep learning approaches like Convolutional Neural Networks(CNN)
2	Movie Recommender System Using K-Nearest Neighbors Variants	Sonu Airen, Jitendra Agrawal	Recommendation done using k- Nearest Neighbor algorithm

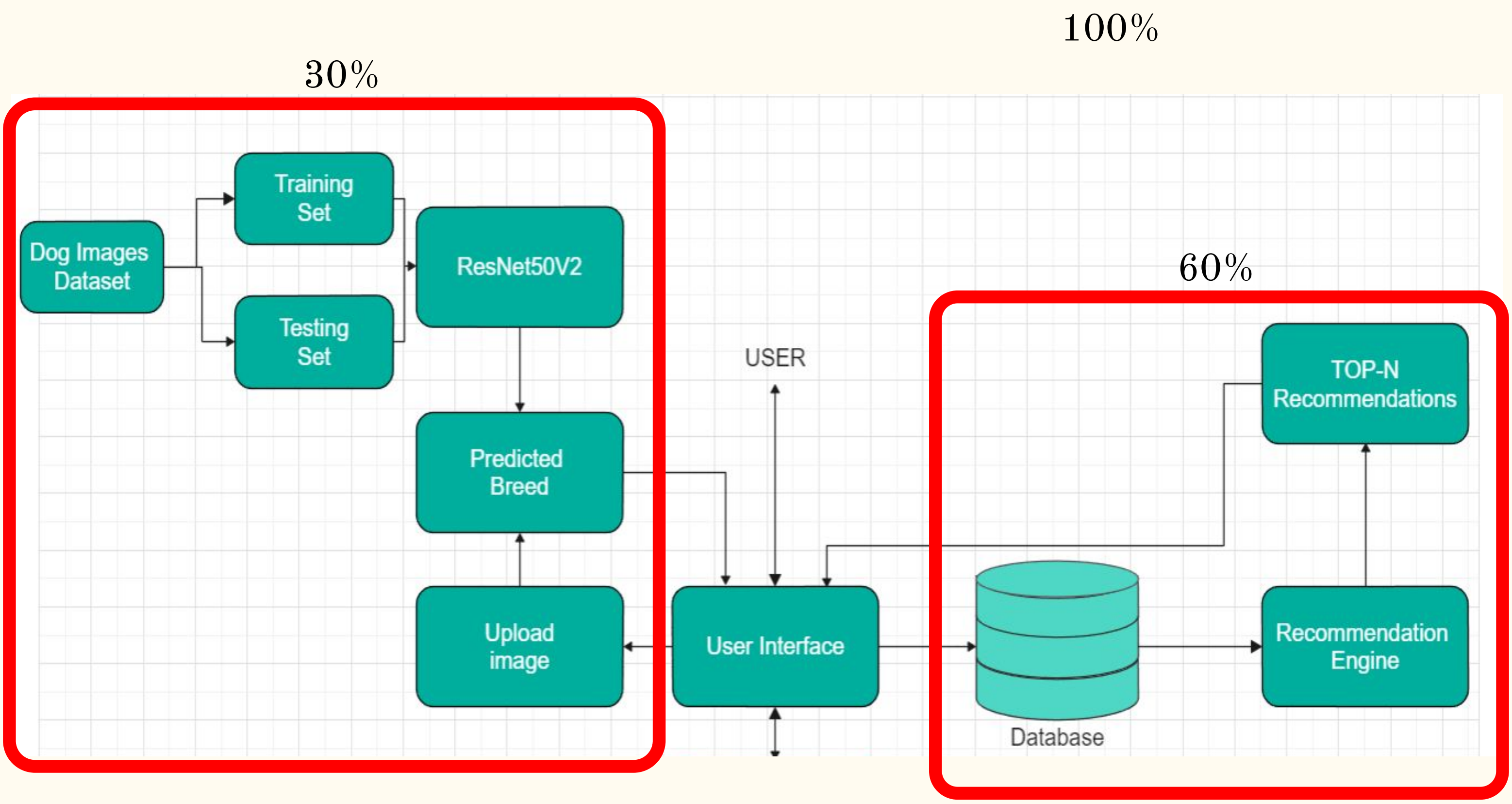
SL.NO	TITLE	AUTHORS	METHODOLOGY
1	Deep viewing for the identification of Covid-19 infection status from chest X-Ray image using CNN based architecture	Partho Ghose, Md. Ashraf Uddin, Uzzal Kumar Acharjee, Selina Sharmin	The methods used in the deep learning approach for Covid-19 detection using convolution neural network
2	A Robust Face Recognition Method Combining LBP with Multi-mirror Symmetry for Images with Various Face Interferences	Shui-Guang Tong, Yuan-Yuan Huang, Zhe-Ming Tong	This method is implemented by combining multi-mirror symmetry with local binary pattern, ie multi-mirror local binary pattern
3	Face Recognition Based Dog Breed Classification Using Coarse-to-Fine Concept and PCA	Massinee Chanvichitkul, Pinit Kumhom, Kosin Chamnongthai	The Principle Component Analysis (PCA) is applied to finely classifying the dog breed.
4	Dog Breed Classification Using Part Localization	Jiongxin Liu, Angjoo Kanazawa, David Jacobs, Peter Belhumeu	The face detector is a SVM regressor with greyscale SIFT descriptors as features.
5	Dog Identification using Soft Biometrics and Neural Networks	Kenneth Lai, Xinyuan Tu, Svetlana Yanushkevich	Uses Soft Biometrics and CNN to identify dogs and their classification

SL.NO	TITLE	AUTHOR	METHODOLOGY
1	Animal species detection and classification framework based on modified multi-scale attention mechanism and feature pyramid network	Chiagoziem C. Ukwuomaa, Zhiguang Qina.	Multi-scale attention mechanism and feature pyramid network
2	A survey of deep neural network architectures and their applications	Weibo Liu, Zidong Wang, Xiaohui Liu.	Discusses some widely-used deep learning architectures and their practical applications.
3	Detecting Objects in Context with Skip Pooling and Recurrent Neural Networks	Sean Bell, C. Lawrence Zitnick,Kavita Bala.	Present the Inside-Outside Net (ION), an object detector that exploits information both inside and outside the region of interest
4	Wild Animal Detection from Highly Cluttered Images Using Deep Convolutional Neural Network	Gyanendra K. Verma* and Pragya Gupta	These features from cluttered images are extracted using Deep Convolutional Neural Network.
5	Recurrent Attention Convolutional Neural Network for Fine-grained Image Recognition	Jianlong Fu, Heliang Zheng, Tao Mei	Recurrent attention convolutional neural network (RA-CNN) which recursively learns discriminative region attention

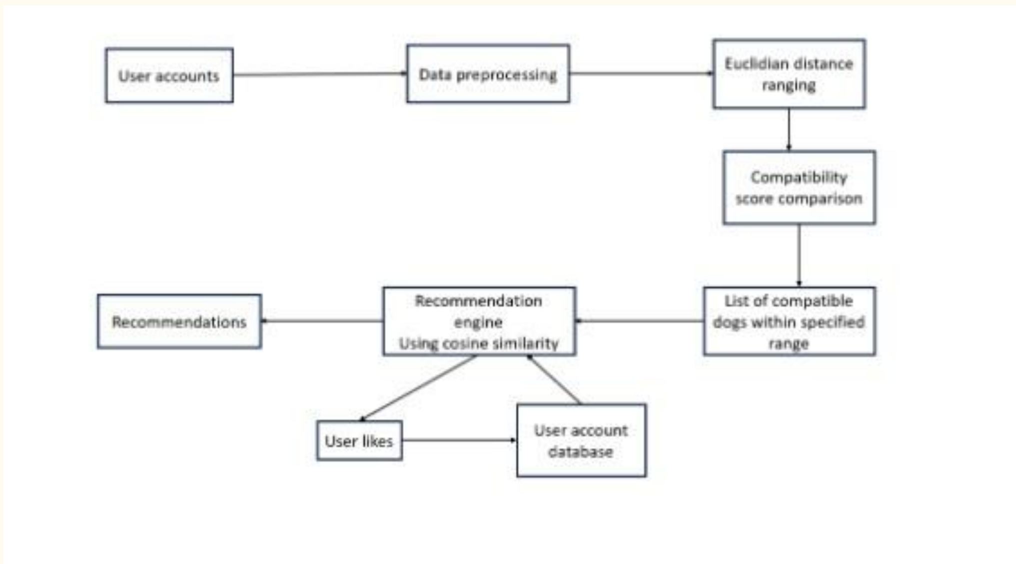
TITLE	AUTHOR	METHOD USED
Adaptive KNN-Based Extended Collaborative Filtering Recommendation Services	Luong Vuong Nguyen , Quoc-Trinh Vo and Tri-Hai Nguyen	Uses K-nearest neighbor (KNN)-based collaborative filtering algorithm for a recommendation system
A Survey of Recommender Systems Based on Deep Learning	Ruihui Mu, Xiaoqin Zeng , Lixin Han	Deep learning based recommender systems
Deep Neural Networks for YouTube Recommendations	Paul Covington, Jay Adams, Emre Sargin	Deep candidate generation model and a separate deep ranking model.
Collaborative Knowledge Base Embedding for Recommender Systems	Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian	Knowledge Base Embedding,collaborative filtering.
A hybrid collaborative filtering method for recommendation in E-Commerce	Yu Lia, Liu Lub , Li Xuefeng	Collaborative filtering,Analyzes the user-item matrix to identify similarity of target item to other items.

SL.NO	TITLE	AUTHOR	METHODOLOGY
1.	A collaborative filtering recommendation system with dynamic time decay	Yi-Cheng Chen, Lin Hui	Recommendation using Dynamic Decay Collaborative Filtering
2.	A k-NN method for lung cancer prognosis with the use of a genetic algorithm for feature selection	Negar Maleki , Yasser Zeinali , Seyed Taghi Akhavan Niaki	Enhanced k-NN method using a genetic algorithm for feature selection
3.	Crop Recommender System Using Machine Learning Approach	Shilpa Mangesh Pande, Dr. Prem Kumar Ramesh	Recommendation using Support Vector Machine, Artificial Neural Network, Random Forest, Multivariate Linear Regression, and K-Nearest Neighbour
4.	Phishing website detection using support vector machines and nature-inspired optimization algorithms	Sagnik Anupam, Arpan Kumar Kar	Detection using Support Vector Machines using optimization algorithms like Bat, Firefly, Grey Wolf and Whale optimization algorithms
5.	Crop Yield Prediction Using Random Forest Algorithm	Namgiri Suresh, N.V.K.Ramesh, Syed Inthiyaz, P. Poorna Priya	Recommendation done using Random Forest Regression algorithm

METHODOLOGY



RECOMMENDATION ENGINE



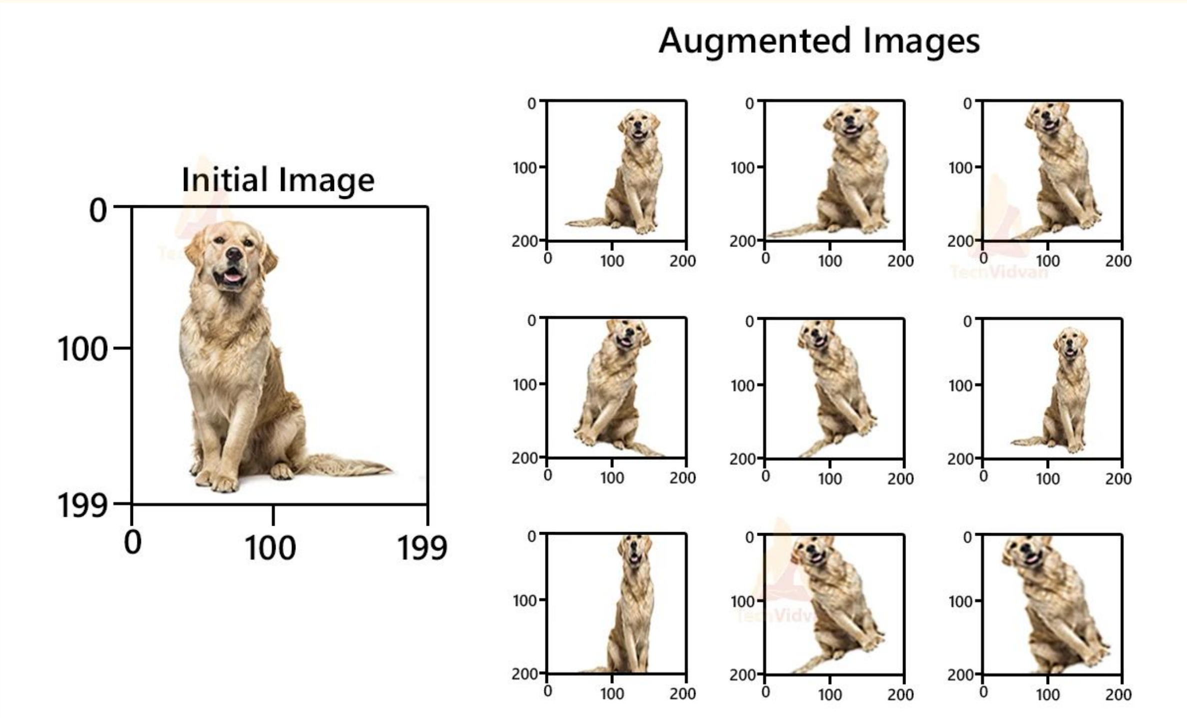
WORK DONE
30% EVALUATION

DOG BREED CLASSIFICATION

- Dataset : The Stanford Dogs dataset contains images of 120 breeds of dogs from around the world.
- Encoding and Scaling Data :
  - We utilize the imread() function from the OpenCV library to read our images which returns images in the form of Numpy arrays, representing height, width, and channels.
  - Due to variations in image dimensions, we resize all images to a uniform size of 224x224 pixels
  - We scale all pixel values within the range of -1 to 1 using the preprocess_input() function.
  - We will split our model into training and testing sets in the ratio of 80:20.

DOG BREED CLASSIFICATION

- Augmentation : Apply various augmentation techniques to create diverse training images.
  - Rotation Range: Random rotation up to 45 degrees.
  - Width and Height Shift Range: Shift images horizontally and vertically by up to 20%.
  - Shear Range: Apply shear transformation with a maximum shear intensity of 20%.
  - Zoom Range: Randomly zoom into images by up to 25%.
  - Horizontal Flip: Flip images horizontally.
  - Fill Mode: Strategy for filling in newly created pixels.



DOG BREED CLASSIFICATION

- Build the Model:

ResNet50V2 Initialization: Here, we initialize the ResNet50V2 model with the specified input shape of our image array (mxnx3 dimensions), where mxn represents the height and width of the image, and 3 represents the RGB channels. We set weights='imagenet' to use the pre-trained weights from the ImageNet dataset. By setting include_top=False, we exclude the top (fully connected) layer.

Freezing Layers: In transfer learning, we freeze the weights of the pre-trained layers to prevent them from being updated during training. This ensures that the pre-trained weights, learned from the ImageNet dataset, are retained. We iterate through all layers in the ResNet50V2 model and set trainable=False to freeze them.

Global Average Pooling and Batch Normalization: We add a Batch Normalization layer to normalize the activations of the previous layer. This helps stabilize and speed up the training process. Then, we add a Global Average Pooling 2D layer to reduce the spatial dimensions of the feature maps and generate a fixed-size representation for each feature map. This reduces the number of parameters in the model and helps prevent overfitting. Finally, we apply dropout regularization with a dropout rate of 0.5 to reduce overfitting by randomly dropping out 50% of the neurons during training

DOG BREED CLASSIFICATION

Fully Connected Layer: We add a fully connected layer with 1024 neurons and ReLU activation function. This layer helps in learning complex patterns from the extracted features. Again, we apply dropout regularization with a dropout rate of 0.5.

Output Layer: Finally, we add an output layer with the number of neurons equal to the number of dog breeds in our dataset. We use the softmax activation function to convert the raw model output into probabilities for each breed class. The model is then created by specifying the inputs (resnet.input) and outputs (predictions).

DOG BREED CLASSIFICATION

- Training :

  Training utilizes RMSprop optimizer with a learning rate of 0.001 on 64-image batches for 20 epochs. Augmentation techniques enhance generalization by creating modified versions for diverse feature learning.

- Model Evaluation and Accuracy:

  The trained model attains an accuracy of 80.50% in distinguishing among 120 dog breeds. Saved components include the model, optimizer, metrics, and weights for future use.

WORK DONE 60% EVALUATION

WORK DONE (60% EVALUATION)

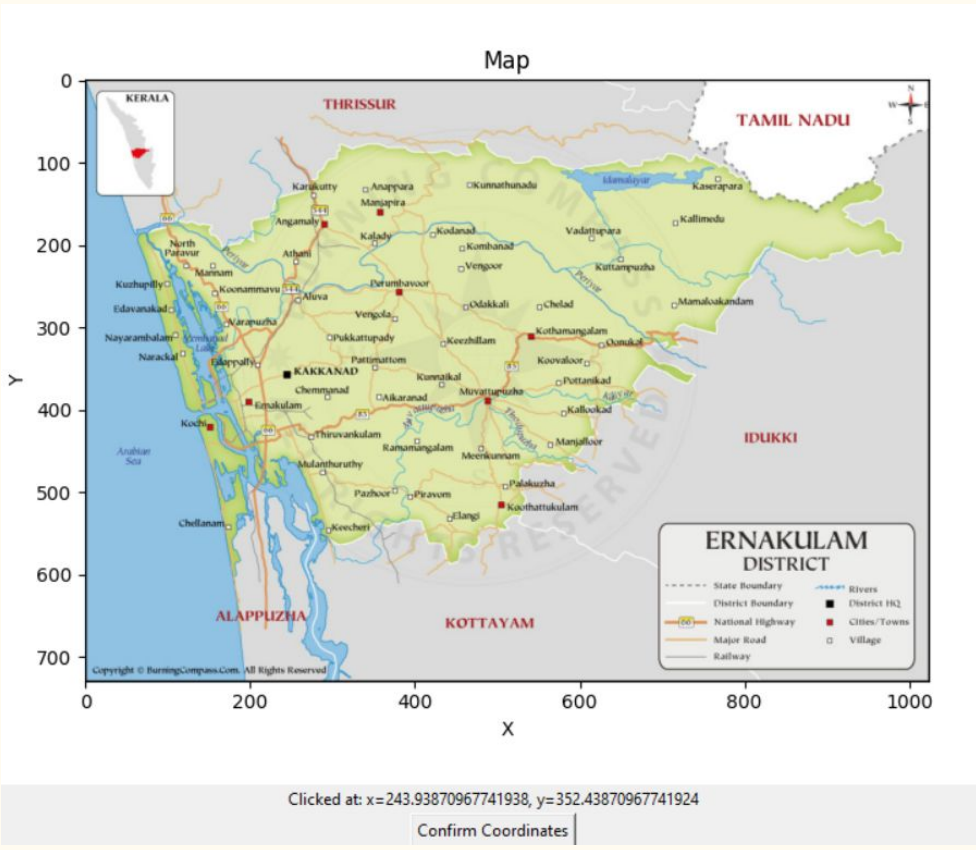
- We have implemented a simple recommendation system using python and mysql.
- We have considered a dataset that contain the breed compatibility score(https://www.friendsofthedog.co.za/breed-compatibility.html) which is made by considering all the factors that needs to be considered while choosing the most appropriate dog breed to get healthier puppies.
- We are implementing a simple algorithm that **clusters other users** to recommend for breeding using the method of euclidean distance.

Breed Compatibility Score

Golden Retriever	Golden Retriever	10
Labrador	Golden Retriever	10
Labrador	Labrador	10
Airedale	Golden Retriever	9
Airedale	Labrador	9
Alaskan Malamute	Siberian Husky	9
American Cocker Spaniel	Italian Greyhound	9
American Cocker Spaniel	Whippet	9
Basenji	Basenji	9
Beagle	Beagle	9
Beagle	Golden Retriever	9
Beagle	Greyhound	9
Beagle	Italian Greyhound	9
Beagle	Labrador	9
Beagle	Saluki	9
Beagle	Whippet	9
Border Collie	Boxer	9
Border Collie	German Shepherd	9
Border Collie	Great Dane	9
Border Collie	Sheltie-Shetland Sheepdog	9
Boston Terrier	Chihuahua	9
Boston Terrier	Chinese Crested	9
Boston Terrier	Dachshund	9
Boston Terrier	English Springer Spaniel	9
Boston Terrier	French bulldog	9
Boston Terrier	Golden Retriever	9
Boston Terrier	Great Dane	9

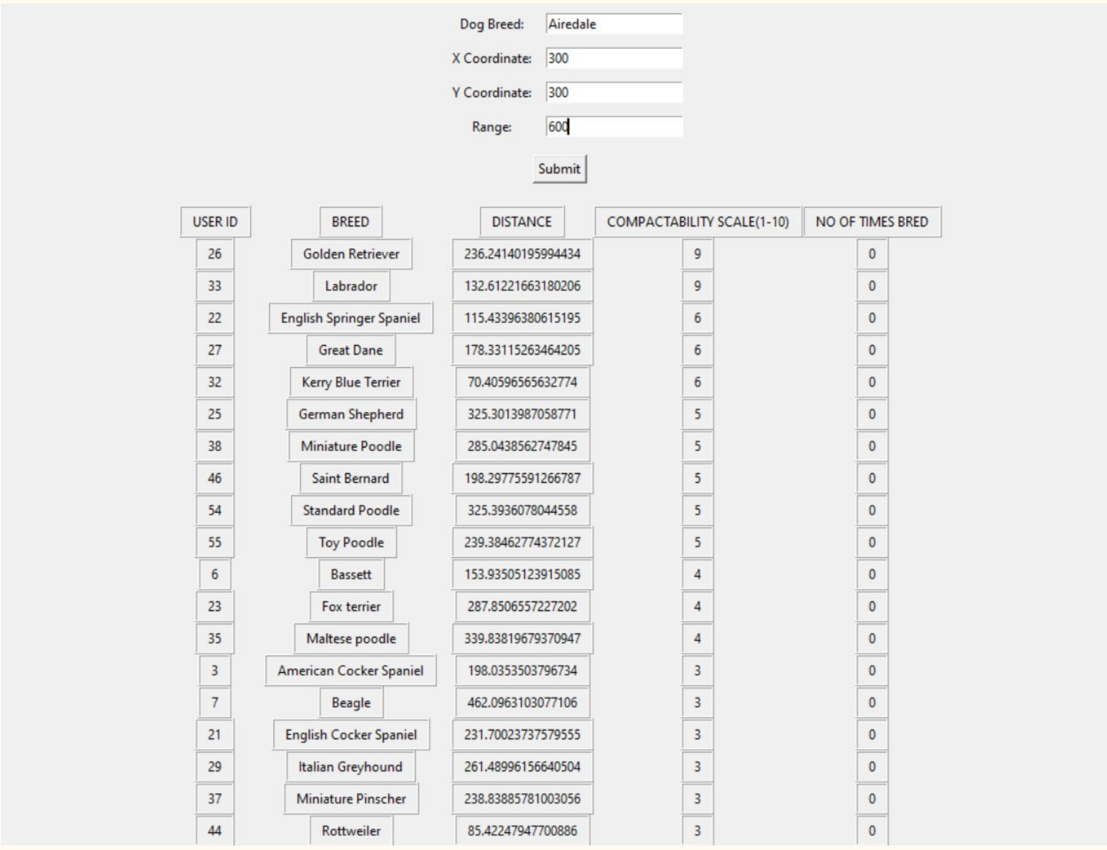
WORK DONE (60% EVALUATION)

- At first we request the users geo location using google maps APIs.
- And using the map feature we get the **latitude and longitude** information provided by the user.
- And similarly we have a database that contain the location information of all other users.
- Once the user specifies the range, the algorithm finds the **euclidean distance** between the user and other users and filter out the ones that has distance more than the range.



WORK DONE (60% EVALUATION)

- And from the filtered we sort the list in the **decreasing order** of the **compactibility score**.
- Content based filtering is then implemented onto this filtered list.
- Issue with content based filtering is availability of historical data.



Dog Breed: Airedale

X Coordinate: 300

Y Coordinate: 300

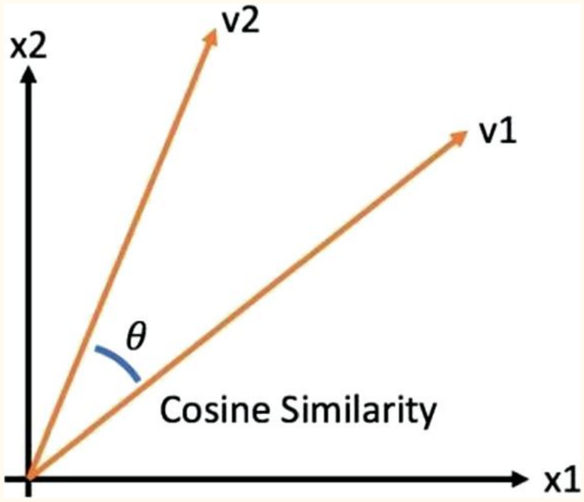
Range: 600

Submit

USER ID	BREED	DISTANCE	COMPACTABILITY SCALE(1-10)	NO OF TIMES BRED
26	Golden Retriever	236.24140195994434	9	0
33	Labrador	132.61221663180206	9	0
22	English Springer Spaniel	115.43396380615195	6	0
27	Great Dane	178.33115263464205	6	0
32	Kerry Blue Terrier	70.40596565632774	6	0
25	German Shepherd	325.3013987058771	5	0
38	Miniature Poodle	285.0438562747845	5	0
46	Saint Bernard	198.29775591266787	5	0
54	Standard Poodle	325.3936078044558	5	0
55	Toy Poodle	239.38462774372127	5	0
6	Bassett	153.93505123915085	4	0
23	Fox terrier	287.8506557227202	4	0
35	Maltese poodle	339.83819679370947	4	0
3	American Cocker Spaniel	198.0353503796734	3	0
7	Beagle	462.0963103077106	3	0
21	English Cocker Spaniel	231.70023737579555	3	0
29	Italian Greyhound	261.48996156640504	3	0
37	Miniature Pinscher	238.83885781003056	3	0
44	Rottweiler	85.42247947700886	3	0

WORK DONE (60% EVALUATION)

- Form the previously created list, we find the similarity between the list and list of all users.
- The features used for finding the similarity are the characteristics of the dogs.



WORK DONE (60% EVALUATION)

- Breed (Textual)
- Gender (Textual)
- Age (Numerical)
- Height (Numerical)
- Weight (Numerical)
- Expectancy (Numerical)
- Group (Textual)
- Grooming Frequency Value (Numerical)
- Grooming Frequency Category (Textual)
- Shedding Value (Numerical)
- Shedding Category (Textual)
- Energy Level Value (Numerical)
- Energy Level Category (Textual)
- Trainability Value (Numerical)
- Trainability Category (Textual)
- Demeanor Value (Numerical)
- Demeanor Category (Textual)

Steps

1. An initial list is produced by comparing the compatibility score and the Euclidean distance
2. The produced list contains the features as mentioned before.
3. These features are converted into corresponding ascii values and concatenated into a numerical string.
4. All the users from the user list are also read and converted to numbers.
5. These numerical values of different features are used as axis in finding the cosine similarity between each records that the user liked and the records that are in the database which contain the details of all the users.
6. The similarities cover is calculated and top 5 or 6 dogs are recommended to the user for each record in the liked records.

WORK DONE
100% EVALUATION

WORK PROGRESS(100% EVALUATION)

- The user can ask the application to provide the most suitable dog for the breeding ,once this request is an acknowledged Recommendation engine starts working and the most suitable dog breed which can be bread with the dog to get the most healthiest puppies are recommended.
- For the future scope of this project we can also implement a module which helps the users to sell and adopt the dogs by specifying their needs

RESULT(100% EVALUATION)

- Develop a page where users can register and login while keeping in mind the age restrictions
- Integrating the classification model and verifying the breed mentioned by the user
- Integrating the recommendation system with the web app
- Implementing the safety features which restricts a profile to be matched more than once a year

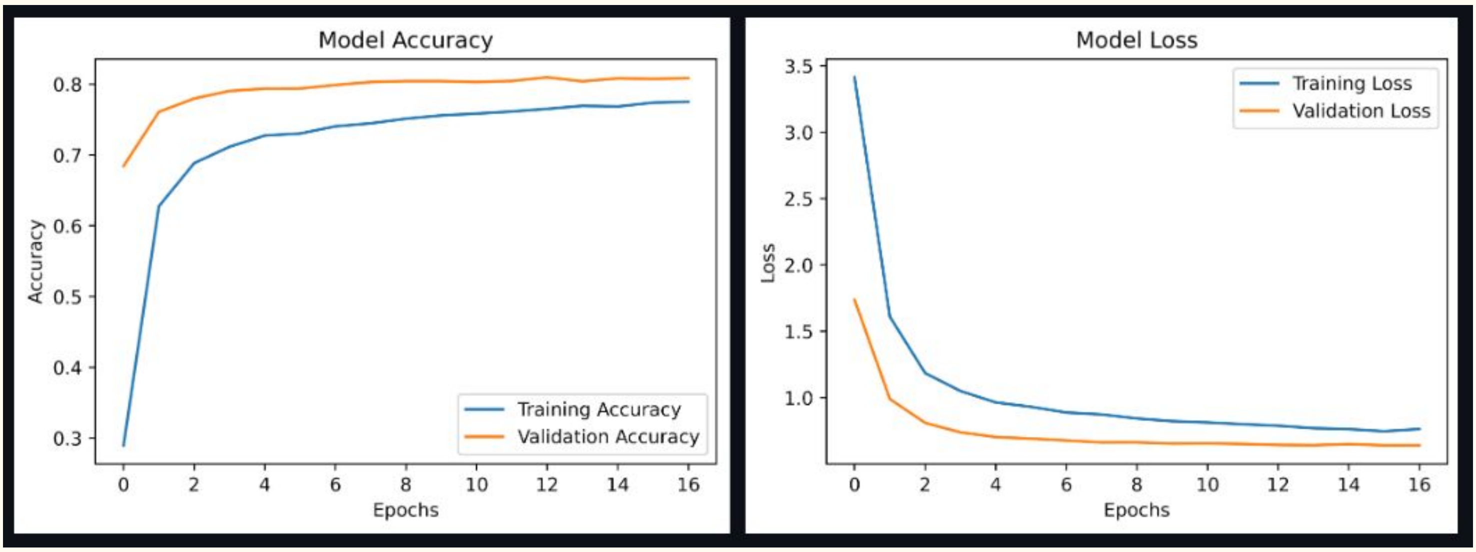
RESULTS

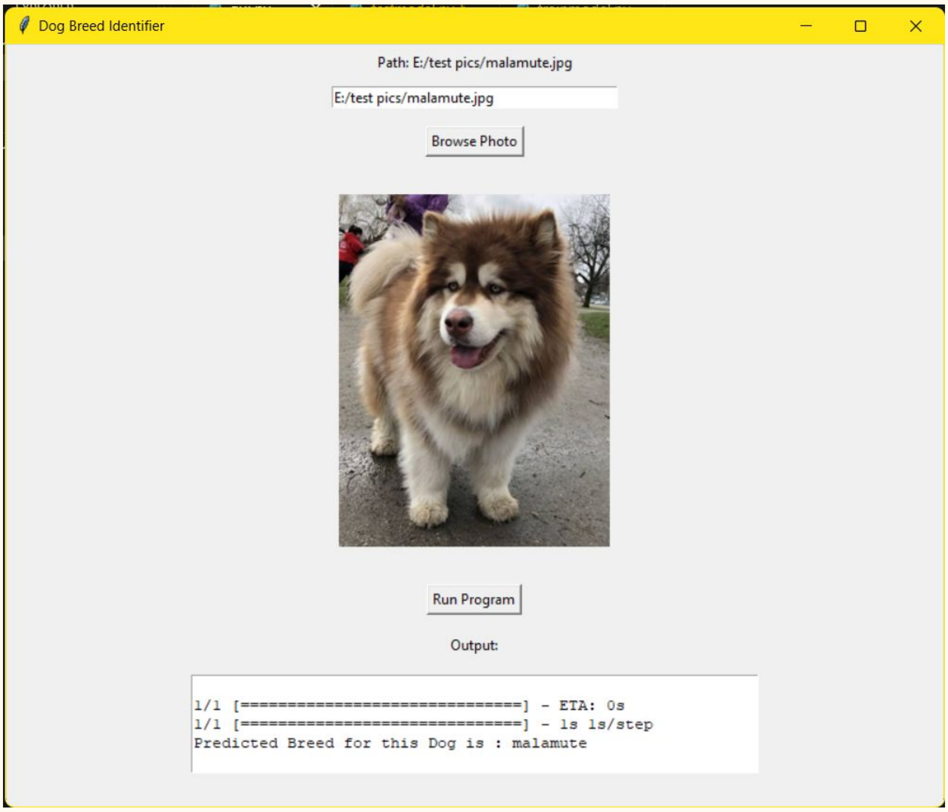
30% EVALUATION

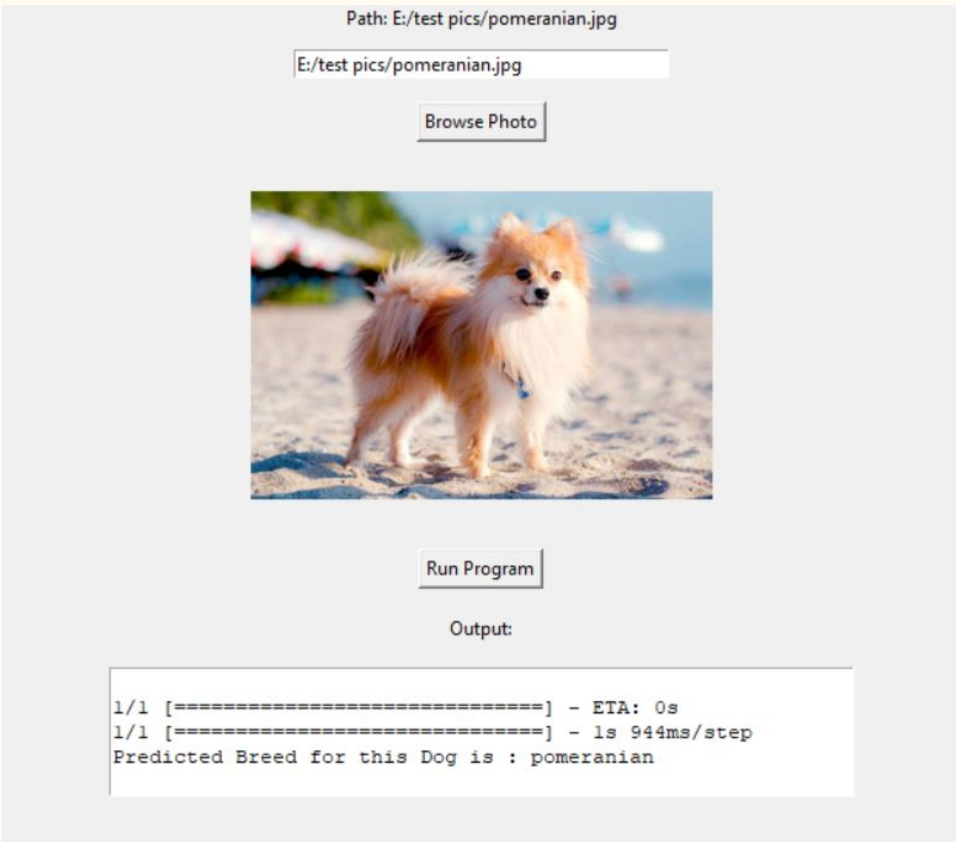
Result (30%)

```
Epoch 14/20
64/64 [==============================] - 57s 888ms/step - loss: 0.7355 - accuracy: 0.7760 - val_loss: 0.7189 - val_accuracy: 0.7979
Epoch 15/20
64/64 [==============================] - 57s 890ms/step - loss: 0.7000 - accuracy: 0.7821 - val_loss: 0.7163 - val_accuracy: 0.7998
Epoch 16/20
64/64 [==============================] - 58s 902ms/step - loss: 0.6872 - accuracy: 0.7868 - val_loss: 0.7308 - val_accuracy: 0.8027
Epoch 17/20
64/64 [==============================] - 58s 898ms/step - loss: 0.6798 - accuracy: 0.7937 - val_loss: 0.7465 - val_accuracy: 0.8037
Epoch 18/20
64/64 [==============================] - 58s 897ms/step - loss: 0.6778 - accuracy: 0.7961 - val_loss: 0.7468 - val_accuracy: 0.7920
Epoch 19/20
64/64 [==============================] - 57s 888ms/step - loss: 0.7084 - accuracy: 0.7888 - val_loss: 0.7390 - val_accuracy: 0.7979
Epoch 20/20
64/64 [==============================] - 57s 894ms/step - loss: 0.6405 - accuracy: 0.8050 - val_loss: 0.7505 - val_accuracy: 0.7920
```

Result (30%)




Dog Breed Identifier
Path: E:/test pics/malamute.jpg
E:/test pics/malamute.jpg
Browse Photo
Run Program
Output:
1/1 [==============================] - ETA: 0s
1/1 [==============================] - 1s 1s/step
Predicted Breed for this Dog is : malamute


Path: E:/test pics/pomeranian.jpg
E:/test pics/pomeranian.jpg
Browse Photo
Run Program
Output:
1/1 [==============================] - ETA: 0s
1/1 [==============================] - 1s 944ms/step
Predicted Breed for this Dog is : pomeranian

60% EVALUATION

Sorted and filtered list according to the distance and compactibility score

	sno INTEGER	breed1 TEXT	euclidean_distance REAL	breed2 TEXT	compatibility_score INTEGER ↓	bn INTEGER
1	26	Airedale	236.24140195994434	Golden Retriever	9	0
2	33	Airedale	132.61221663180206	Labrador	9	0
3	22	Airedale	115.43396380615195	English Springer S…	6	0
4	27	Airedale	178.33115263464205	Great Dane	6	0
5	32	Airedale	70.40596565632774	Kerry Blue Terrier	6	0
6	25	Airedale	325.3013987058771	German Shepherd	5	0
7	38	Airedale	285.0438562747845	Miniature Poodle	5	0
8	46	Airedale	198.29775591266787	Saint Bernard	5	0
9	54	Airedale	325.3936078044558	Standard Poodle	5	0
10	55	Airedale	239.38462774372127	Toy Poodle	5	0
11	6	Airedale	153.93505123915085	Bassett	4	0
12	23	Airedale	287.8506557227202	Fox terrier	4	0
13	35	Airedale	339.83819679370947	Maltese poodle	4	0
14	3	Airedale	198.0353503796734	American Cocker Sp…	3	0
15	7	Airedale	462.0963103077106	Beagle	3	0
16	21	Airedale	231.70023737579555	English Cocker Spa…	3	0
17	29	Airedale	261.48996156640504	Italian Greyhound	3	0
18	37	Airedale	238.83885781003056	Miniature Pinscher	3	0
19	44	Airedale	85.42247947700886	Rottweiler	3	0
20	56	Airedale	291.10994486619654	Weimaraner	3	0
21	57	Airedale	316.5706872090339	Whippet	3	0
22	4	Airedale	308.60330523181375	American Staffords…	2	0
23	5	Airedale	260.16341018675166	Basenji	2	0
24	12	Airedale	352.20448605888026	Boxer	2	0
25	14	Airedale	47.43416490252569	Bulldog	2	0
26	18	Airedale	188.22327167489146	Dachshund	2	0
27	28	Airedale	184.74306482247175	Greyhound	2	0
28	34	Airedale	501.5974481593781	Malinois	2	0

Results (60% EVALUATION)

A	B	C	D	E	F G	H	I	J	K	L	M
id	breed	name	gender	age	description	temperament	temperam	height	weight	expectancy	group
1	Affenpinscher	Max1	m	10	The Affenâ€™s apish	Friendly, Active, Outgoing	1	52	30	12	Sporting Group
2	Affenpinscher	Max2	m	12	The Affenâ€™s apish	Friendly, Active, Outgoing	1	52	31	12	Sporting Group
3	Affenpinscher	Max3	m	7	The Affenâ€™s apish	Friendly, Active, Outgoing	1	51	32	12	Sporting Group
4	Affenpinscher	Max4	m	8	The Affenâ€™s apish	Friendly, Active, Outgoing	1	45	33	12	Sporting Group
5	Affenpinscher	Max5	m	11	The Affenâ€™s apish	Friendly, Active, Outgoing	1	46	34	12	Sporting Group
6	Affenpinscher	Max6	m	10	The Affenâ€™s apish	Friendly, Active, Outgoing	1	47	35	12	Sporting Group
7	Affenpinscher	Max7	m	5	The Affenâ€™s apish	Friendly, Active, Outgoing	1	48	36	12	Sporting Group
8	Affenpinscher	Max8	m	6	The Affenâ€™s apish	Friendly, Active, Outgoing	1	49	26	12	Sporting Group
9	Affenpinscher	jollie1	f	8	The Affenâ€™s apish	Friendly, Active, Outgoing	1	49	27	12	Sporting Group
10	Affenpinscher	jollie2	f	5	The Affenâ€™s apish	Friendly, Active, Outgoing	1	40	28	12	Sporting Group
11	Affenpinscher	jollie3	f	9	The Affenâ€™s apish	Friendly, Active, Outgoing	1	44	29	12	Sporting Group
12	Affenpinscher	jollie4	f	10	The Affenâ€™s apish	Friendly, Active, Outgoing	1	34	29	12	Sporting Group
13	Affenpinscher	jollie5	f	11	The Affenâ€™s apish	Friendly, Active, Outgoing	1	54	30	12	Sporting Group
14	Affenpinscher	jollie6	f	11	The Affenâ€™s apish	Friendly, Active, Outgoing	1	56	31	12	Sporting Group
15	Afghan Hound	john1	m		The Afghan Hound is a	Confident, Courageous, Smart	2	45	40	10	Herding Group
15	Afghan Hound	john2	m		The Afghan Hound is a	Confident, Courageous, Smart	2	46	41	10	Herding Group
15	Afghan Hound	john3	m		The Afghan Hound is a	Confident, Courageous, Smart	2	47	34	10	Herding Group
15	Afghan Hound	john4	m		The Afghan Hound is a	Confident, Courageous, Smart	2	48	35	10	Herding Group
15	Afghan Hound	john5	m		The Afghan Hound is a	Confident, Courageous, Smart	2	49	36	10	Herding Group
15	Afghan Hound	john6	m		The Afghan Hound is a	Confident, Courageous, Smart	2	50	37	10	Herding Group
15	Afghan Hound	john7	m		The Afghan Hound is a	Confident, Courageous, Smart	2	51	38	10	Herding Group
15	Afghan Hound	john8	m		The Afghan Hound is a	Confident, Courageous, Smart	2	52	39	10	Herding Group
15	Afghan Hound	john9	m		The Afghan Hound is a	Confident, Courageous, Smart	2	53	39	10	Herding Group
15	Afghan Hound	john10	m		The Afghan Hound is a	Confident, Courageous, Smart	2	54	38	10	Herding Group
15	Afghan Hound	bella1	f		The Afghan Hound is a	Confident, Courageous, Smart	2	55	37	10	Herding Group
15	Afghan Hound	bella2	f		The Afghan Hound is a	Confident, Courageous, Smart	2	56	36	10	Herding Group
15	Afghan Hound	bella3	f		The Afghan Hound is a	Confident, Courageous, Smart	2	40	35	10	Herding Group
15	Afghan Hound	bella4	f		The Afghan Hound is a	Confident, Courageous, Smart	2	45	34	10	Herding Group

Results (60% EVALUATION)

C	D	E	F	G	H	I	J	K	L	M	N	O	P
name	gender	age	description	temperament score	temperament	temperam	height	weight	expectanc	group	grooming	grooming_frequency_cate	shedding
Max	male	10	The Affenâ€™s apish	1	Confident, Courageous, Smart	2	45	40	10	HerdingGroup	0.4	WeeklyBrushing	0.8
john	male	8	The Afghan Hound is	1	Confident, Courageous, Smart	2	46	39	10	HerdingGroup	0.4	WeeklyBrushing	0.8
Cooper	male	8	American Foxhound	1.2	Agile, Intelligent, Self-Confident	7	15	1	18	ToyGroup	1	Specialty/Professional	0.2
Brenad	male	11	The defining charact	0.8	Affectionate, Playful, Outgoing	20	14	3	18	ToyGroup	0.8	DailyBrushing	0.2
Lucy	female	9	Akitas are burly, hea	1	Confident, Courageous, Smart	2	55	37	10	Herding Group	0.4	Weekly Brushing	0.8

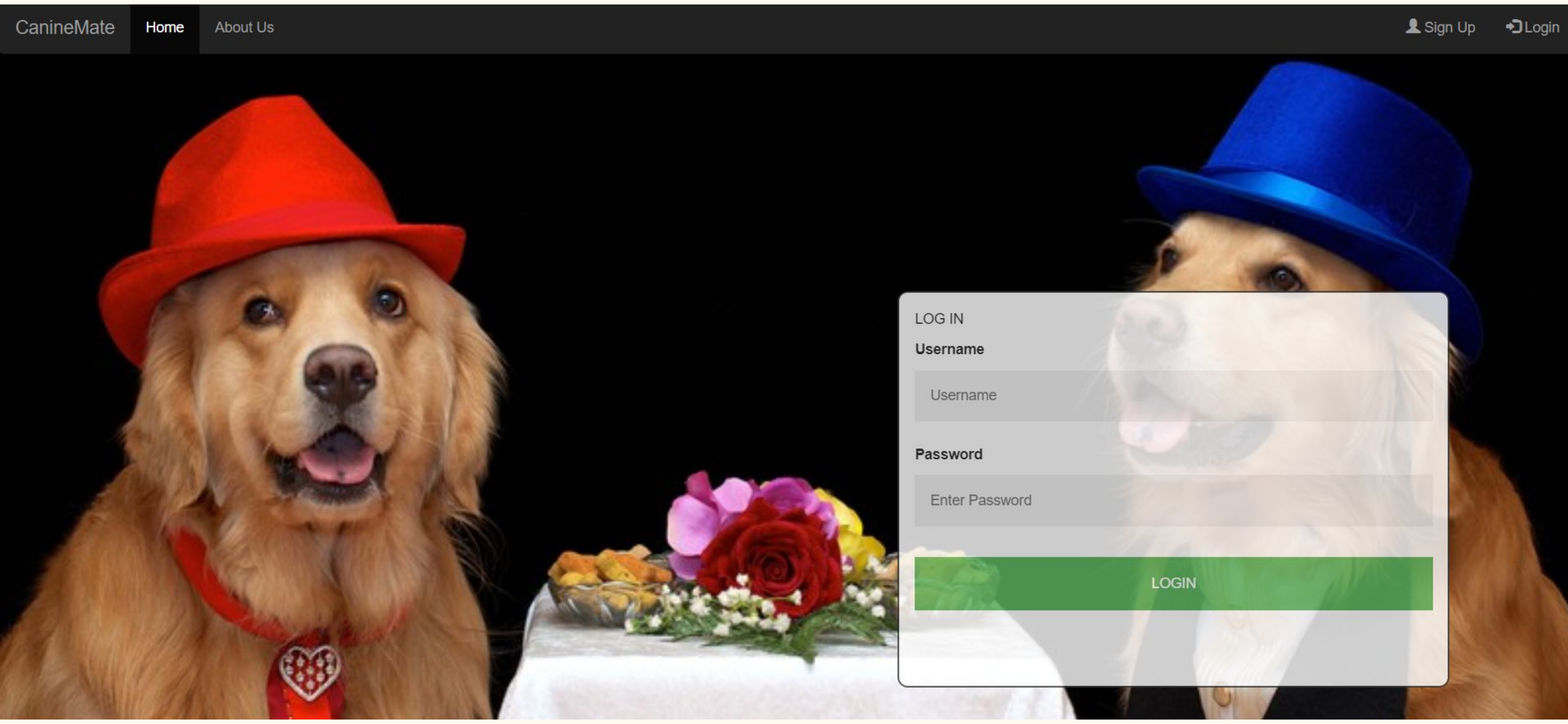
Results (60% EVALUATION)

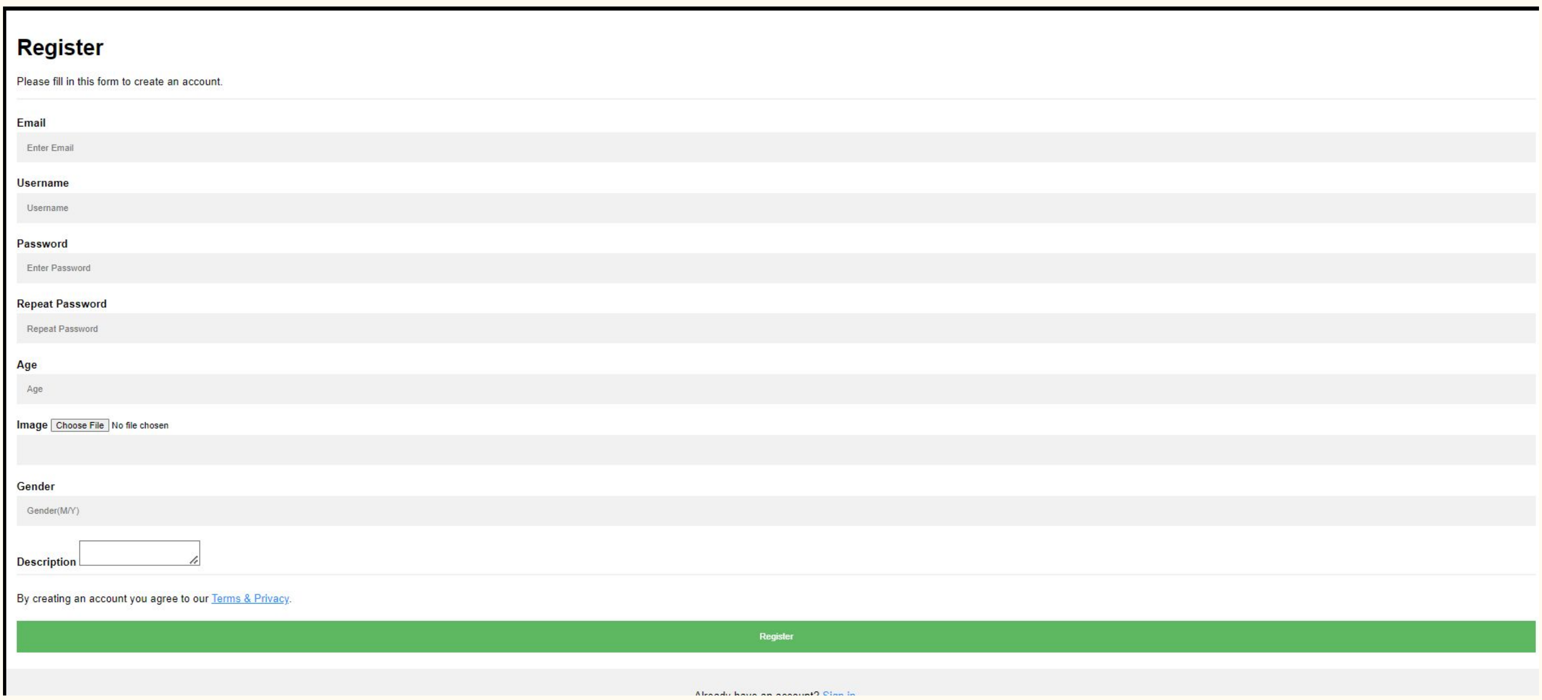
```
Breed: Affenpinscher
Gender: female
Age: 8
Height: 45
Weight: 40
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006

Breed: Affenpinscher
Gender: female
Age: 5
Height: 46
Weight: 41
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006
```

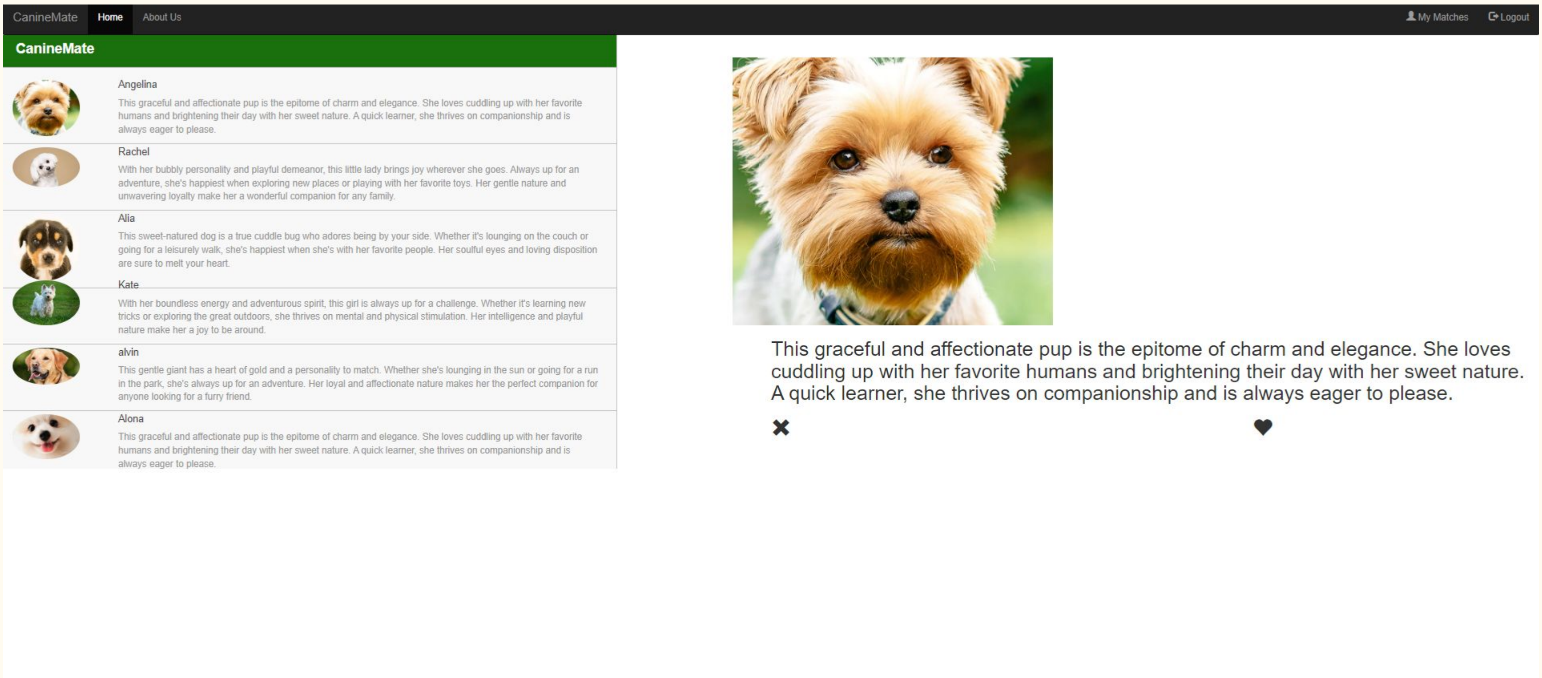
```
Breed: Affenpinscher
Gender: female
Age: 9
Height: 47
Weight: 34
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006

Breed: Affenpinscher
Gender: female
Age: 10
Height: 48
Weight: 35
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006
```

```
Breed: Affenpinscher
Gender: female
Age: 11
Height: 49
Weight: 36
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006

Breed: Affenpinscher
Gender: female
Age: 8
Height: 50
Weight: 37
Group: HerdingGroup
Grooming Frequency Value: 0.4
Grooming Frequency Category: WeeklyBrushing
Shedding Value: 0.8
Shedding Category: Regularly
Energy Level Value: 0.6
Energy Level Category: RegularExercise
Trainability Value: 1.0
Trainability Category: EagertoPlease
Demeanor Value: 0.6
Demeanor Category: Alert/Responsive
ps: 0.9999991228753006
```

100% EVALUATION


CanineMate
Home
About Us
Sign Up
Login
LOG IN
Username
Username
Password
Enter Password
LOGIN


Register
Please fill in this form to create an account.
Email
Enter Email
Username
Username
Password
Enter Password
Repeat Password
Repeat Password
Age
Age
Image Choose File No file chosen
Gender
Gender(M/Y)
Description
By creating an account you agree to our Terms & Privacy.
Register


CanineMate
Home
About Us
My Matches
Logout
CanineMate
Angelina
This graceful and affectionate pup is the epitome of charm and elegance. She loves cuddling up with her favorite humans and brightening their day with her sweet nature. A quick learner, she thrives on companionship and is always eager to please.
Rachel
With her bubbly personality and playful demeanor, this little lady brings joy wherever she goes. Always up for an adventure, she's happiest when exploring new places or playing with her favorite toys. Her gentle nature and unwavering loyalty make her a wonderful companion for any family.
Alia
This sweet-natured dog is a true cuddle bug who adores being by your side. Whether it's lounging on the couch or going for a leisurely walk, she's happiest when she's with her favorite people. Her soulful eyes and loving disposition are sure to melt your heart.
Kate
With her boundless energy and adventurous spirit, this girl is always up for a challenge. Whether it's learning new tricks or exploring the great outdoors, she thrives on mental and physical stimulation. Her intelligence and playful nature make her a joy to be around.
alvin
This gentle giant has a heart of gold and a personality to match. Whether she's lounging in the sun or going for a run in the park, she's always up for an adventure. Her loyal and affectionate nature makes her the perfect companion for anyone looking for a furry friend.
Alona
This graceful and affectionate pup is the epitome of charm and elegance. She loves cuddling up with her favorite humans and brightening their day with her sweet nature. A quick learner, she thrives on companionship and is always eager to please.
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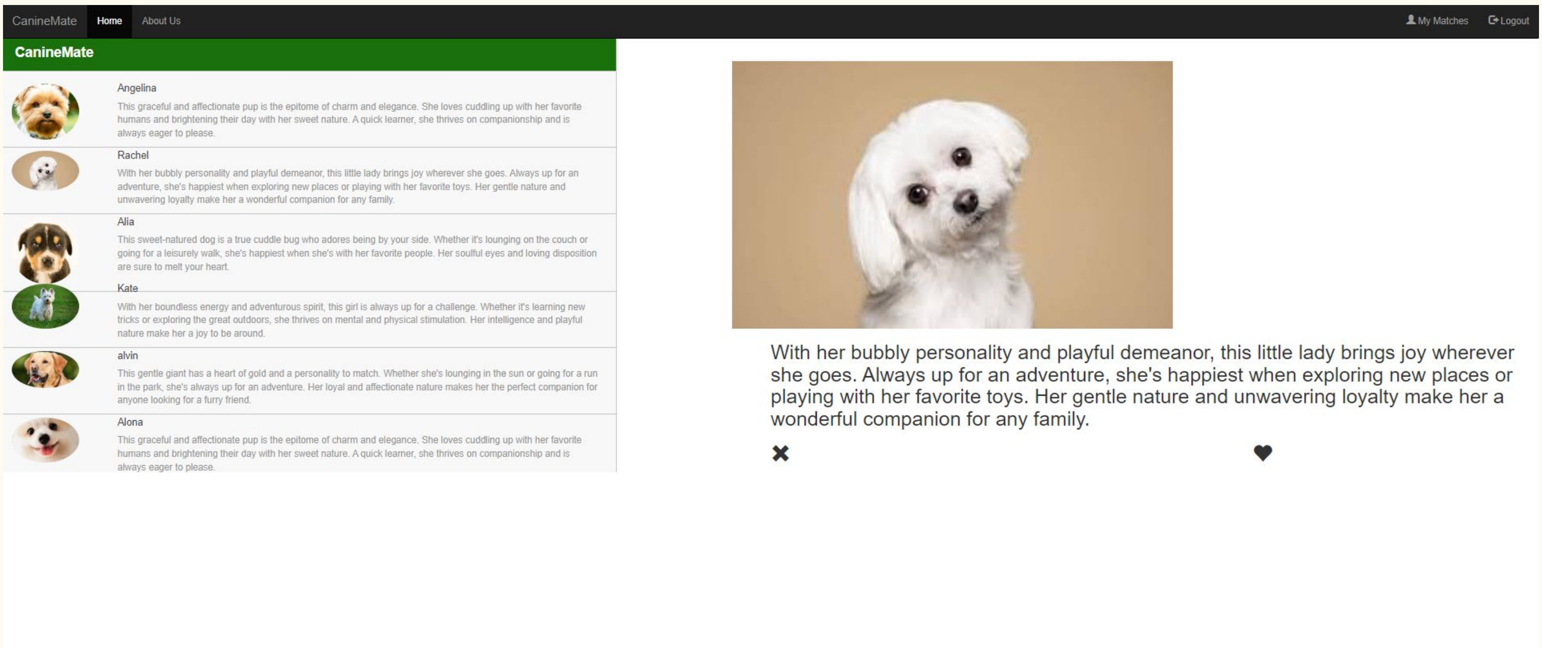
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With her bubbly personality and playful demeanor, this little lady brings joy wherever she goes. Always up for an adventure, she's happiest when exploring new places or playing with her favorite toys. Her gentle nature and unwavering loyalty make her a wonderful companion for any family.

WORK DISTRIBUTION

- Alan Baby George :Database Manipulation(SQL)
- Alen T Babu :Recommendation system(Python)
- Alex Santhosh :Classification model
- Amal Stephen : Front-end ,flask connections

CONCLUSION

In conclusion, the "CanineMate" project represents a visionary endeavor to revolutionize the world of dog breeding and adoption through the development of a sophisticated Android app and an integrated platform. By leveraging cutting-edge image processing technology, advanced compatibility algorithms, "CanineMate" aims to facilitate responsible breeding practices and prioritize the welfare of dogs.

PAPER PUBLICATION

Conference : International Conference on Innovations and Advances in Cognitive Systems 2024

Conference Date: 27-28, May 2024

Link: https://iciacs.com/

Location: Kangayam, Tamil Nadu, India

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Submission 346	
Title	Dog Breed Classification and Recommendation System Using ResNet50 and Cosine Similarity
Paper:	(May 07, 10:42 GMT)
Author keywords	ResNet50v2 Cosine Similarity Recommendation
Abstract	To improve breeding practices and customer happiness, we offer a comprehensive system for classifying dog breeds and personalized profile recommendations. Our method uses the Stanford Dog Dataset and deep learning techniques to accurately categorize dog breeds with the aid of an upgraded ResNet50v2 model.To guarantee the accuracy of user-provided data, we additionally aggregate breed attributes into a CSV file for evaluation.Moreover, our approach uses customized profile recommendations to handle issues with cold start and breeding compatibility.Our method takes user preferences, geographical location, and breeding compatibility into account while utilizing content-based filtering for initial recommendations and incorporating appropriateness rankings from reliable sources. Favourite profiles are refined using cosine similarity and saved in a user-specific database. The experiment's result show that breed categorization can be done quite accurately, user input can be consistently verified, and helpful recommendations may be made. Through the use of data-driven strategies in pet identification systems, this research advances computer vision in pet-related applications and improves breeding outcomes.
Submitted	May 07, 10:42 GMT
Last update	

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first name	last name	email	country	affiliation	Web page	corresponding?
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FUTURE SCOPE

- **Integrating an Adoption Platform** : Create a suitable adoption platform where the users can allow the puppies obtained through successful breeding process to be adopted by other users.
- **Chatbot Integration** : Integrate a chatbot feature where the users can communicate with each other to share details or to obtain more information about their dogs.
- **Education and Training Resources**: Expand the platform to offer educational resources and training modules for both breeders and owners on responsible breeding practices, dog care, and behavior management. This could include video tutorials, webinars, and certification programs.
- **Continuous Improvement and Feedback Mechanisms**: Establish mechanisms for gathering feedback from users to continuously improve the platform's features, usability, and effectiveness in promoting responsible dog breeding and ownership.

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Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
101003/ CS822U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
101003/ CS822U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

101003/ CS822U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
101003/ CS822U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
101003/ CS822U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
101003/ CS822U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
101003/ CS822U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
101003/ CS822U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
101003/ CS822U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
101003/ CS822U.1-PO10	M	Project brings technological changes in society.

101003/ CS822U.1- PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
101003/ CS822U.1- PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
101003/ CS822U.2- PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
101003/ CS822U.2- PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
101003/ CS822U.2- PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
101003/ CS822U.2- PO5	H	Systematic approach is the tip for solving complex problems in various domains.
101003/ CS822U.2- PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
101003/ CS822U.2- PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

101003/ CS822U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
101003/ CS822U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
101003/ CS822U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
101003/ CS822U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
101003/ CS822U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
101003/ CS822U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
101003/ CS822U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
101003/ CS822U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

101003/ CS822U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
101003/ CS822U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
101003/ CS822U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
101003/ CS822U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
101003/ CS822U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
101003/ CS822U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
101003/ CS822U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
101003/ CS822U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
101003/ CS822U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
101003/ CS822U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
101003/ CS822U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
101003/ CS822U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like network design and administration, database design and

		knowledge engineering.
101003/ CS822U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
101003/ CS822U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
101003/ CS822U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
101003/ CS822U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
101003/ CS822U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.
101003/ CS822U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and

		commit to professional ethics and responsibilities and norms of the engineering practice.
101003/ CS822U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
101003/ CS822U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
101003/ CS822U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
101003/ CS822U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
101003/ CS822U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
101003/ CS822U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.