Cat Breed Classification Web App Utilizing Teachable Machine

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Abstract

Cats are widely kept as pets and exhibit diverse physical traits, making breed identification difficult, especially when breeds look similar or image quality is limited. This research develops a web-based cat breed recognition system built with Google's Teachable Machine and trained on images from 15 different breeds. ReactJS is used as the interface layer, while Flask handles the backend operations and model integration. The workflow includes training the model with internal images and validating its performance using external samples to assess robustness. Experimental results indicate that the system can recognize cat breeds with strong performance, reaching 99.52% accuracy for Persian cats and maintaining reliable predictions even when tested on low-quality or imperfect images. Overall, the system offers a practical solution for enthusiasts and researchers to more easily and accurately distinguish various cat breeds.

1. Introduction

In modern life, the cat has become one of the most popular companion animals worldwide. However, identifying a cat's breed is not a simple task. Complex visual variations resulting from differences in pose, lighting, and cross-breeding present a significant challenge, even for experienced cat owners (Juslan & Muhammad, 2025). Accurate breed identification is crucial for providing appropriate care, as each breed has unique characteristics, dietary needs, and predispositions to certain diseases.

The rapid growth of artificial intelligence technologies, especially computation-driven learning methods, have opened up new possibilities in designing automated image-based classification systems (Johannes et al., 2024). One accessible tool is a cloud-accessible platform called Teachable Machine from Google that allows users to build computational learning methods models without demanding technical coding knowledge. By simply uploading labelled data, users can train a model to recognize specific patterns. This platform has proven effective in various applications, from identifying herbal leaves to classifying waste materials (Permatasari, 2024a), demonstrating its potential for application to biological subjects with complex image variations. A previous study emphasizes how computational approaches can help reduce human error in making classification-related decisions (Ahda & Bahri, 2018). Research related to artificial intelligence development in Indonesia continues to grow, especially within natural language studies and visual data analysis (Ahda et al., 2024).The implementation of artificial intelligence in various fields in Indonesia continues to expand, supporting not only technological innovation but also the preservation of local identity and culture through digital applications (Sulistyo et al., 2023). Recent studies have also emphasized the importance of developing

diverse AI datasets in Indonesia to support the advancement of intelligent systems and ensure inclusivity across various domains (Sulistyo et al., 2025).

The urgency of this research lies in the growing public interest in cats and the corresponding need for accurate breed information. Utilizing technology like Teachable Machine, a web-based platform offers an opportunity to deliver a web-based solution that benefits not only cat lovers but also the fields of education, research, and the pet industry. Taking these challenges and opportunities into account, this research is directed toward developing an online-based system cat breed classification solution using the Teachable Machine platform, which is expected to be an effective solution for helping the public recognize the diversity of cat breeds. Digital platforms have been shown to enhance information accessibility and support problem-solving when existing systems are no longer effective (Farokhah et al., 2024).

1.1 Literature Review

Image processing is a field that focuses on manipulating image quality to facilitate interpretation, either by humans or computers. In the context of artificial intelligence, object detection is used to identify an object within predefined classifications. The main challenge in detecting complex visual objects, such as cat breeds, lies in variations of pose, lighting, and inter-breed similarities that can reduce identification accuracy.

Machine learning, particularly supervised learning, enables systems to learn patterns from a training dataset to make predictions on new data. Teachable Machine, an internet-accessible utility from Google , streamlines the process of building classification models without requiring advanced programming skills. This platform leverages transfer learning to accelerate the training process, which typically demands significant computational resources.

Previous studies have demonstrated the effectiveness of Teachable Machine across various domains. (Johannes et al., 2024) successfully applied it to mineral rock identification, (Permatasari, 2024) utilized it for herbal leaf image recognition, and other researchers implemented it for waste classification.

2. Research Methods
2.1 Image Processing

In the digital technology era, images often require specific processing to appear clearer, sharper, and more informative. This process, known as image processing, aims to enhance the quality of digital images by addressing issues such as noise, excessive color, or blurriness (Peryanto et al., 2020). Through this process, images become easier to analyze, both for humans and machines.

One of the key applications of image processing is object detection, which involves recognizing and classifying objects into specific categories. In this study, object detection is utilized to identify plant seedlings and compare them with predefined plant categories. The comparison results serve as the basis for determining whether the detected seedling belongs to a particular plant category.

However, the main challenge in object detection lies in the presence of overlapping objects, where one object may be partially covered or positioned close to another within the image. This condition can reduce the accuracy of the identification process. To overcome this issue, various object detection methods are employed, each offering distinct advantages and limitations in achieving more precise identification.

2.2 Similarity Learning

Supervised learning is a learning method that utilizes two types of data: a training dataset and a testing dataset (Peryanto et al., 2020). Similarity learning is considered part of supervised learning in machine learning . It shares conceptual similarities with regression and classification, yet its core purpose is to develop a similarity function that evaluates the degree of relation between two objects related or how similar they are. A similarity function produces a value that quantifies the degree of similarity between two objects. Although there is no single definitive definition for measuring similarity, it is generally inversely related to distance metrics. This technique assigns higher values when objects are similar and zero or negative values when they are highly dissimilar.

In the process of similarity learning for classification, pairs of similar objects (x_1, x_2^+) and dissimilar objects (x_i, x_i^-) are obtained. There is an equation involving (x_{i1}, x_{i2}) that is provided along with a binary label $\in \{0,1\}$, which indicates whether the objects are similar or not. The objective is to establish a classifier capable of determining whether a given pair of objects shares similarity. Fig 1 below illustrates the process of similarity learning.
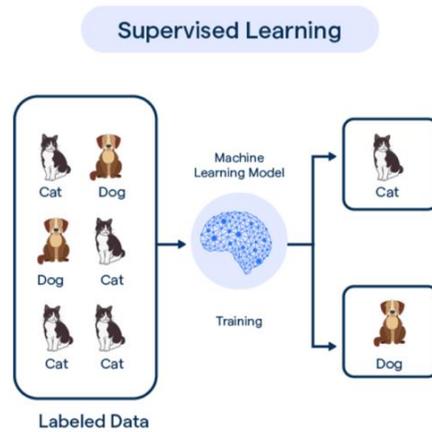

Fig 1. Illustration of the Supervised Learning Process

2.3 Teachable Machine
Teachable Machine is a browser-accessible a platform that enables its users to construct classification models Built by Google quickly and easily for machine learning application development (Pujari et al., 2022)(Peryanto et al., 2020) . Built by Google , this platform utilizes computational learning techniques to examine data without the need for manual coding. Teachable Machine can process various types of data such as images, audio, and motion, making it suitable for students, educators, designers, and anyone interested in understanding artificial intelligence concepts and building their own classification models.

In this study, Teachable Machine is used to detect cat breeds based on uploaded images. The training process involves collecting multiple images of cats from different breeds, poses, and angles. Each breed requires a wide range of image variations to enable the model to distinguish differences more accurately. The more data used, the longer the training time required to produce a well-performing classification model. Fig 2 below illustrates the data training process in Teachable Machine for cat breed detection.
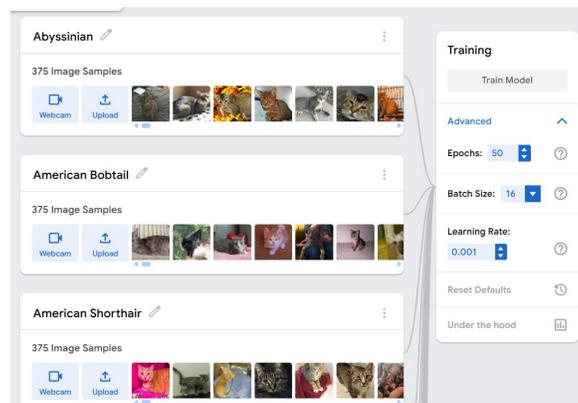

Fig 2. Training Process Using Teachable Machine

2.4 ReactJS

ReactJS is a front-end library developed by Facebook, widely used to support web framework development (Wali & Ahmad, 2018). This technology has gained popularity due to its speed, simplicity, and high scalability in building user interfaces. By using ReactJS, developers can create interactive, stateful, and reusable UI components, making the application development process more efficient and well-structured.

In the Model-View-Controller (MVC) architecture, ReactJS functions in the View layer, which is responsible for displaying data and handling user interactions (Nursaid et al., n.d. 2022). Moreover, ReactJS facilitates dynamic interface updates without the need without refreshing the whole page, which improves speed and responsiveness.

2.5 Flask

Flask is a simple and highly flexible Python-based micro web application framework designed to simplify backend development and API-based service integration. This framework enables efficient communication between the server and frontend interfaces such as React, making it widely used as a bridge between machine learning models and web applications. With built-in library support, a routing system, and seamless data exchange using the JSON format, Flask efficiently accelerates the process of integration and web-based application development (Jonathan & Setiyawati, 2023).

3. Result and Discussion

The application development process consists of the following stages: (1) Object Data Collection; (2) Training Process Using Teachable Machine; (3) Model Conversion; (4) Application Interface Development; and (5) Testing.

3.1 Object Data Collection

The image dataset employed in this research were obtained from the Gano Cat Breed Image Collection, which consists of 5.625 images with varying resolutions. The dataset includes 15 cat breed classes, such as Abyssinian, American Bobtail, Bengal, Maine Coon, Persian, and others. Each breed contains 375 images. These images were selected to represent visual variations covering differences in posture, lighting environments, and surrounding contexts. the image data in the dataset.
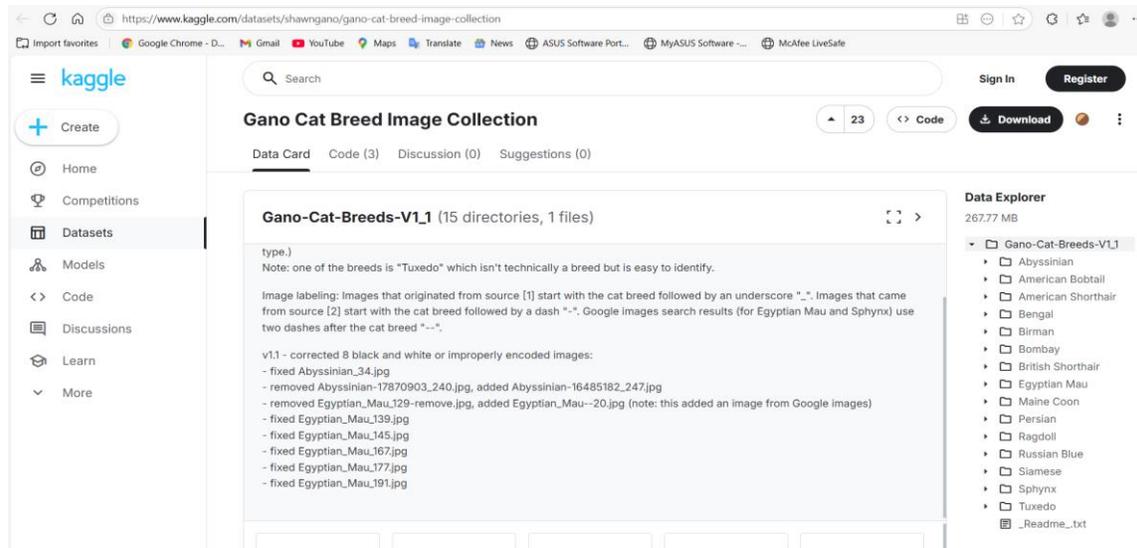

Fig 3. Gano Cat Breed Image Dataset sourced from Kaggle

Specifically, the dataset's image collection can be described as follows:

Table 1. Details of Cat Breed Classes in the Dataset

No	Cat Breed Class	Number of Images
1	Abyssinian	375
2	American Bobtail	375
3	American Shorthair	375
4	Bengal	375
5	Birman	375
6	Bombay	375
7	British Shorthair	375
8	Egyptian Mau	375
9	Maine Coon	375
10	Persian	375
11	Ragdoll	375
12	Russian Blue	375
13	Siamese	375
14	Sphynx	375
15	Tuxedo	375
Total		**5.625**

3.2 Model Training with the Teachable Machine Platform

The training procedure involved uploading the images to the Teachable Machine platform and organizing the data into classes representing different cat breeds. The model was trained using the following parameters:

Table 2. Model Training Parameters

Type of Stage	Description
Total Epochs	50 Epochs
Batch Amount	size 16
Rate	set to 0.001

The model was trained automatically through a supervised learning method. Each image was labeled accordingly, enabling the algorithm to recognize the unique attributes associated with each breed. During the training process, the model demonstrated stable convergence and consistently increasing accuracy values.
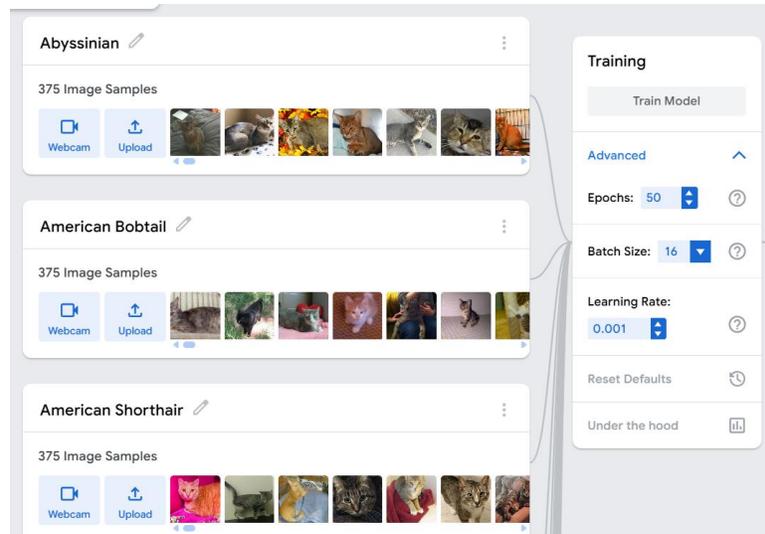
Fig 4. Teachable Machine Training Interface for Cat Breed Classification

From the training results, it was observed that the Persian breed achieved the highest accuracy (99.52%), while other breeds also achieved high accuracy levels above 97%.
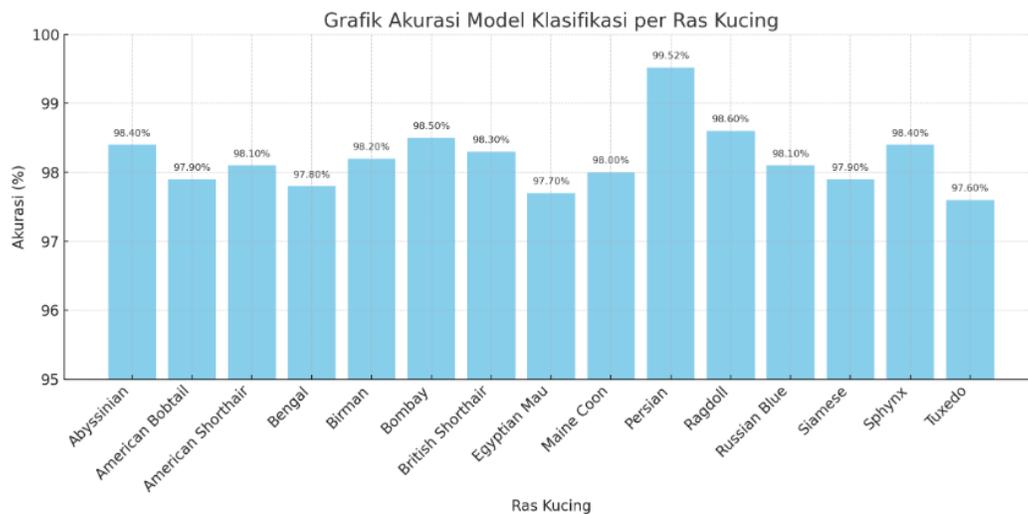

Fig 5. Accuracy Results of the Cat Breed Classification Model

3.3 Model Export and Integration into the Website

After completing the training phase carried out with Teachable Machine, the next stage was model export and integration. The model output was exported as a TensorFlow (.h5) file to be deployed in a web environment and then integrated using the Flask framework as the backend API. This integration allows the model to interact with the web application efficiently and systematically through request and response processes.

3.4 User Interface Development with ReactJS

The user interface (UI) was developed using ReactJS to enable users to upload cat images and view classification results directly.
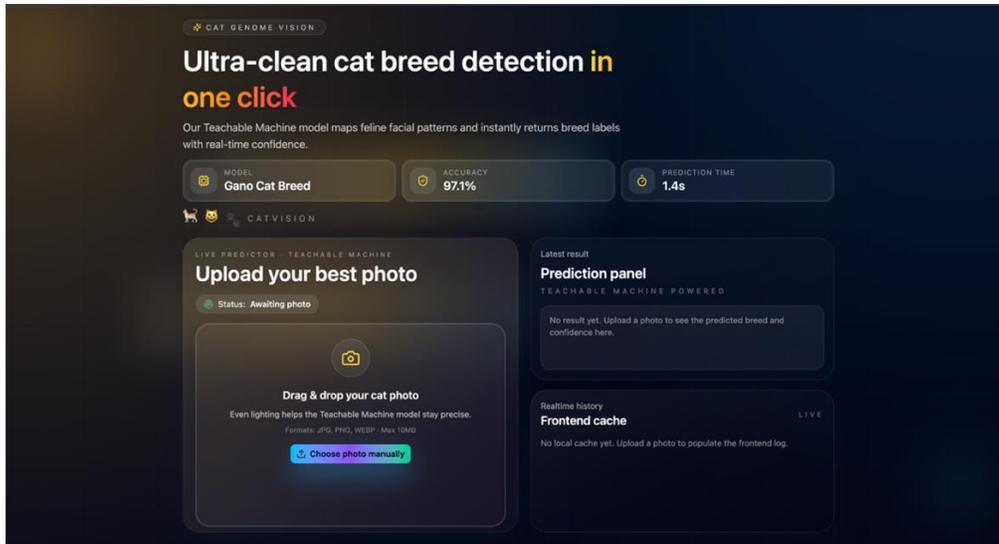
Fig 6. Preview of the Cat Breed Detection Interface

The classification results are displayed in real-time, accompanied by the accuracy level shown as a percentage.

3.5 Testing Result

Testing was conducted using several cat images from external sources to assess the model's performance beyond such The system's architecture was developed using ReactJS to handle the user interface layer. training data. The purpose was to ensure that the model could perform effectively under real-world conditions with variations in lighting, pose, and image quality. One test example used a blurred WhatsApp sticker image that contained visual noise and foreign objects covering part of the cat's face. The model successfully identified the Persian breed with an accuracy of 77.63%, demonstrating its tolerance to visual noise and its ability to recognize general breed characteristics effectively.
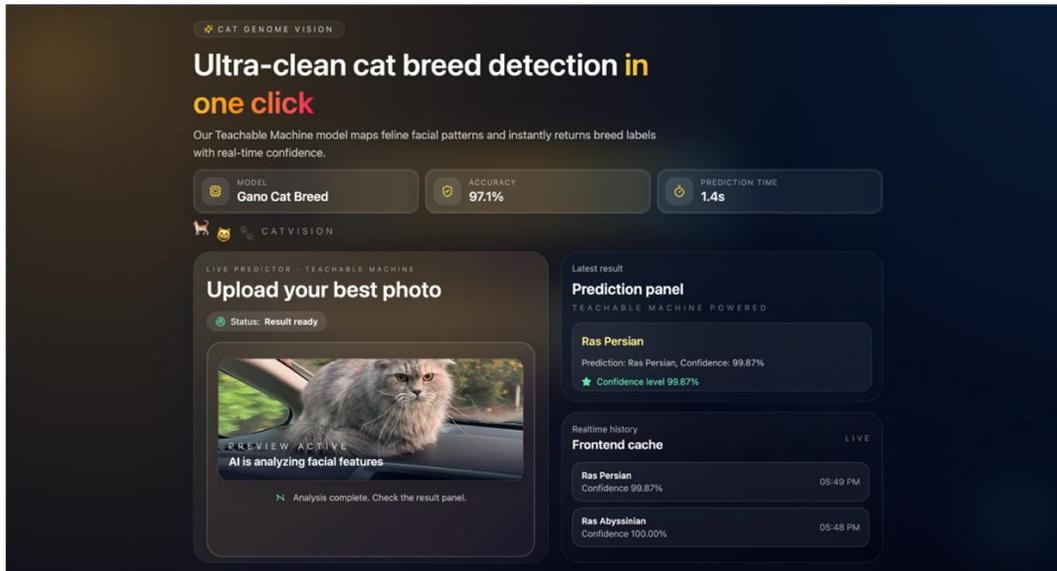

Fig 7. Result of Cat Breed Detection Using an External Image

The following table summarizes the testing results of several images obtained from outside the dataset:

Table 3. Summary of Model Testing on External Images

No	Image Source	Actual Breed (Estimated)	Model Prediction	Accuracy	Analysis
1	WhatsApp Sticker (screenshot)	Persian	Persian	77,63%	The image is slightly blurred with yellowish lighting and a toy mask covering part of the cat's face. Despite the visual noise, the model successfully recognized the main features of the Persian breed.
2	Smartphone Camera (Indoor)	British Shorthair	British Shorthair	100,00%	The image is sharp with sufficient lighting and a frontal pose. The model was able to identify it with perfect accuracy.
3	Google images	British Longhair	Persian	76,08%	Both breeds have highly similar visual characteristics. The model misclassified the image due to nearly identical facial structure and fur color.

Based on the testing results using images from outside the dataset, it can be concluded that the system demonstrates good capability in recognizing cat breeds even under non-ideal image conditions, although with slightly lower accuracy compared to testing with the training dataset. Several key factors contributing to mismatches or reduced accuracy include:

1. Low image quality
   Blurry or low-resolution images make it difficult for the model to read distinctive facial features of cats.
2. Suboptimal lighting
   Yellowish, dark, or overexposed lighting conditions can alter the visual appearance of fur texture and color.
3. Uncommon poses
   Images captured from non-frontal angles or cats standing upright can affect the classification outcome.
4. Foreign objects on the cat's face
   Items such as toy masks or other elements around the face can interfere with the detection of key features.
5. Visual similarities between breeds
   Some breeds, such as British Shorthair and American Shorthair, share highly similar visual characteristics, making them prone to misclassification.

Despite several mispredictions, these results still indicate that the developed system has strong classification capability and responsiveness. It also shows potential for further enhancement to improve adaptability when handling diverse real-world images.

4. Conclusions

Based on the results of the study, a web-based cat breed classification system was successfully developed using Teachable Machine as the model training platform. The system was structured with ReactJS on the frontend and Flask handled the backend, functioning as a bridge between the model and the web application through API integration. The model was trained using the Gano Cat Breed Image Collection dataset, which consists of 15 cat breeds, with training parameters of 50 training cycles, batch size 16, and learning rate 0.001. This the model training procedure a stable a TensorFlow model in .h5 format ready to be used for automatic cat breed image classification.

The testing results showed that for internal test data, the model reached an accuracy of 99.52% for the Persian breed, while for external data such as smartphone photos and WhatsApp sticker screenshots, the system was still able to perform classification, although with varying accuracy due to lighting, camera angle, and image

quality factors. Despite the system's good performance, evaluation was limited to accuracy level only, as Teachable Machine does not yet support advanced evaluation measures including confusion matrix, precision, recall values and the F1-score in terms of user-friendliness. The evaluation was conducted descriptively based on the correspondence between prediction results and actual labels, revealing that the model tends to rely heavily on the visual composition of the image, including lighting and the presence of distracting objects.

For further development, it is recommended that the model be retrained using more diverse real-world data and employ CNN architectures such as Mobile Net, Residual, or Efficient Net to improve accuracy and robustness against visual noise. In addition to technical evaluation, usability testing was conducted with 12 general users and 2 cat experts, who gave an average score above 4.5 regarding usability, clarity of results, and interface layout. These findings indicate that the system is not only functionally reliable but also responsive to user needs, providing a strong foundation for future development to ensure broader and more dependable real-world applications.

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