Performance Analysis of Image Prediction using Keras and Gradio: A Comparative Study

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ABSTRACT

This research titled "Performance Analysis of Image Prediction using Keras and Gradio: A Comparative Study" aims to analyze and compare the performance of image prediction using two specific frameworks, Keras and Gradio.

The study evaluates the effectiveness and efficiency of both frameworks in accurately predicting images. Testing is conducted by training and evaluating deep learning models using a dataset of images collected from 10 different animal species, with each species having 5 sample images, resulting in a total of 50 animal images tested.

The research also compares various architectures and optimization techniques to enhance the predictive capabilities of the models. Performance metrics considered in the study include accuracy and training time.

The results show that using Gradio for image prediction yields faster processing times compared to Keras. The average processing time using Gradio is 1.2 seconds, while with Keras, it is 3.36 seconds. Furthermore, Gradio achieves a higher accuracy rate, with 360 out of 500 (72%) correct answers, whereas Keras only reaches 345 out of 500 (69%) correct answers.

These findings demonstrate that Gradio performs better in terms of accuracy and processing efficiency compared to Keras in the task of image prediction for similar animal categories. The results of this research can provide valuable insights for researchers and practitioners in selecting the most suitable framework for image prediction projects involving similar animal species.

Keywords
Image; keras; gradio;

1. INTRODUCTION

In recent years, advancements in deep learning (1) and computer vision have revolutionized the field of image prediction, enabling sophisticated models to accurately classify and recognize objects within images (2). Among the various frameworks available for developing image prediction models (3), Keras (4) and Gradio (5) have emerged as two prominent choices due to their ease of use and powerful capabilities. The effectiveness and efficiency of these frameworks in predicting images have been extensively studied in different contexts. However, there remains a need for a direct comparison of their performance, particularly in tasks involving similar animal categories.

This research titled "Performance Analysis of Image Prediction using Keras and Gradio: A Comparative Study" aims to address this gap by conducting an in-depth examination of the two frameworks in the context of image prediction for similar animal species (6). The study's primary objective is to evaluate and compare the effectiveness and efficiency of Keras and Gradio in accurately predicting images of distinct animal categories while shedding light on their respective strengths and limitations (7-9). The research involves training and evaluating deep learning models on a carefully curated dataset comprising 50 images of ten different animal species (10-11). Each species is represented by five sample images, ensuring a balanced and diverse dataset. Throughout the study, various architectural configurations and optimization techniques are explored to enhance the models' predictive capabilities. To assess the performance of Keras and Gradio, key performance metrics are considered, including accuracy and training time (12-14). Accuracy measures the models' ability to correctly classify images, while training time evaluates the efficiency of each framework in processing and learning from the dataset (15).

Through this comparative study, valuable insights are provided into the capabilities of Keras and Gradio in handling image prediction tasks involving similar animal categories. The findings from this research can be of great significance to researchers and practitioners seeking to develop efficient and accurate image prediction systems in the field of computer vision (16). Furthermore, the outcomes of this study have the potential to inform decision-making processes when selecting the most appropriate framework for specific image prediction tasks, especially those concerning similar animal species. This, in turn, can contribute to the advancement of computer vision technology, enhancing the development of innovative applications across various industries.

In the subsequent chapters of this research, methodologies employed will be detailed, experimental results presented, and the implications of findings discussed. By the conclusion of this study, the aim is to contribute valuable knowledge to the image prediction domain and foster the development of sophisticated frameworks that can accurately identify and classify images of similar animal categories.

2. METHODOLOGY

The methodology (17) employed in this study aims to conduct a comprehensive performance analysis of image prediction using Keras and Gradio frameworks for similar animal categories.

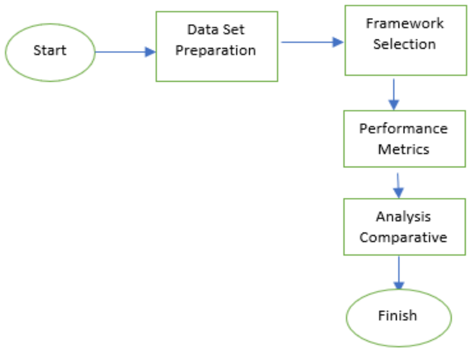

Fig 1: Flowchart for Research Design

From figure 1 This section outlines the step-by-step approach utilized to evaluate the effectiveness and efficiency of the frameworks in predicting images accurately.

2.1 Dataset Preparation

The dataset used in this study was obtained from the Kaggle website and comprises 50 images of animals grouped into 10 distinct animal species, namely Antelope, Bear, Cat, Dog, Eagle, Fox, Gorilla, Horse, Jellyfish, and Kangaroo (18). Each image is labeled with its corresponding animal species, and the dataset is further organized with unique file names for each image. Below is Antelope image from the dataset as shown fig 2.

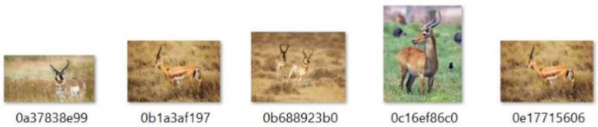

Fig 2: Antelope Image Sourced from Kaggle.com

Prior to model training, the dataset underwent preprocessing steps to ensure consistency and quality. To facilitate evaluation, the dataset was randomly split into training and testing sets, with careful consideration to maintain proportional representation of each animal species in both sets. Stratified sampling was utilized to ensure class balance in the splits. The images were transformed into suitable formats for the Keras and Gradio frameworks. In Keras, the images were converted to NumPy (19) arrays and reshaped to the expected input dimensions for deep learning models, while in Gradio, The "classify_image" function is integrated into the Gradio interface, allowing users to upload an image and obtain the top predictions from the pre-trained ResNet50 model (20-21). The Gradio interface is set up to take an image as input and provide text output, displaying the top predictions with their corresponding confidence scores. Data verification was carried out by manually inspecting a subset of images and labels to ensure accuracy and proper preprocessing. These rigorous data preparation steps ensure that the dataset is robust and ready for training and evaluating deep learning models using both Keras and Gradio frameworks, enabling a comprehensive comparative study on image prediction performance for similar animal categories.

2.2 Framework Selection

This research aims to perform a performance analysis of image prediction using two frameworks, namely Keras and Gradio. The data consists of 50 images of animals grouped into 10 different animal species. In the data preparation phase, the dataset of images is processed and normalized to ensure consistency and quality.

Once the data is ready, the next step involves framework setup and model selection. The code is for Keras image classification using TensorFlow with the ResNet101 model. The ResNet101 model is a deep convolutional neural network widely used for image recognition tasks (22). It loads a pre-trained ResNet101 model with weights from the "imagenet" dataset.

The code defines a function called "classify_image" to classify an input image passed as "img_path." The image is loaded and preprocessed using the "image.load_img" and "preprocess_input" functions from the Keras library. The preprocessed image is then fed into the ResNet101 model using "model.predict" to obtain the predictions for the top three most probable classes. To make the predictions interpretable, the code uses the "decode_predictions" function from Keras, which maps the model's numerical predictions back to human-readable class labels along with their corresponding probabilities. The top three predictions are stored in the "results" list as tuples of (label, probability). This code enables accurate image classification and can be used to identify the top three most probable classes for an input image using the ResNet101 model.

Fig 3: Python Image Preprocessing

```
img_preprocessed =
preprocess_input(np.expand_dims(img_
array, axis=0))
```

Gradio image classification is using Gradio and TensorFlow with the ResNet50 model. Gradio is used to create an interactive web-based interface for image prediction.

The code loads a pre-trained ResNet50 model with weights from the "imagenet" dataset, which is a widely used deep convolutional neural network for image recognition tasks. The function "classify_image" takes an input image as a numpy array and preprocesses it using Keras functions. The image is then fed into the ResNet50 model for prediction. The top three most probable classes are obtained using the "de code_predictions" function from Keras, which maps the model's numerical predictions back to human-readable class labels along with their corresponding probabilities. The predictions are formatted as a list of strings containing the label and confidence percentage.

Fig 4: Python classify_image Script

```
img = image.array_to_img(input_image)
```

The Gradio interface is set up with the "gr.Interface" function, specifying "classify_image" as the classification function, "image" as the input type, and "text" as the output type. The interface is titled "Image Classification" and provides a description prompting users to upload an image and get the top predictions. By launching the Gradio interface, users can interactively upload images and receive real-time predictions

for the top three most probable classes, making image classification accessible and user-friendly.

After the testing process is completed, the performance results of the Keras model with Gradio are analyzed and compared with the general performance of Keras. The findings and insights from this analysis provide valuable information for researchers and practitioners in selecting the most suitable framework for image prediction projects involving similar animal categories. Thus, this research contributes knowledge and guidance in choosing the Keras and Gradio frameworks for image prediction tasks with optimal efficiency and accuracy.

2.3 Testing and Implementation Prediction

Table 1. Outcome in the Gradio Framework

Type of Animal	Test Result					
	Pic 1	Pic 2	Pic 3	Pic 4	Pic 5	Avg.
Antelope	0a37838e99.jpg	0b1a3af197.jpg	0b688923b0.jpg	0c16ef86c0.jpg	0e17715606.jpg	
Accuracy	gazelle: 82.08%	gazelle: 91.67%	impala: 65.61%	impala: 64.02%	gazelle: 79.49%	25
Timing (sec)	3	1	2	1	1	1.6
Bear	0e6a8744de.jpg	0f6b575750.jpg	0f61069510.jpg	1b890605d5.jpg	1ebb88dff2.jpg	
Accuracy	hook: 5.52%	brown_bear: 99.98%	brown_bear: 99.95%	American_black_bear: 99.88%	brown_bear: 96.86%	40
Timing (sec)	1	1	1	1	1	1
Cat	0b54dde5f5.jpg	0c3d04bcf5.jpg	0cfaf08fce.jpg	0d0d6d90d8.jpg	1a2dce7848.jpg	
Accuracy	tabby: 80.49%	clog: 65.10%	theater_curtain: 18.70%	tiger_cat: 81.48%	Egyptian_cat: 41.48%	30
Timing (sec)	1	1	1	1	1	1
Dog	0a73823599.jpg	0b6670809d.jpg	0be3797d3d.jpg	0d33157df8.jpg	0df912089d.jpg	
Accuracy	wire-haired_fox_terrier: 32.44%	Great_Dane: 40.87%	Doberman: 100.00%	flat-coated_retriever: 94.07%	Labrador_retriever: 56.08%	50
Timing (sec)	1	1	1	1	1	1
Eagle	0a249855c4.jpg	0df14cf243.jpg	0e6ba163a7.jpg	1d28265409.jpg	2bc02045e9.jpg	
Accuracy	bald_eagle: 80.69%	bald_eagle: 98.90%	bald_eagle: 99.87%	bald_eagle: 99.99%	bald_eagle: 96.93%	50
Timing (sec)	2	1	1	1	2	1.4
Fox	0a9a650a0b.jpg	0ae0157e0c.jpg	0cfb16f2dd.jpg	0f47a9d345.jpg	1a89f88226.jpg	
Accuracy	red_fox: 93.69%	red_fox: 62.14%	red_fox: 95.73%	grey_fox: 76.26%	gazelle: 19.09%	40
Timing (sec)	3	1	3	1	1	1.8
Gorilla	0a70a1128f.jpg	0f31875d98.jpg	01a857d803.jpg	1ad709457f.jpg	1c82894bb8.jpg	
Accuracy	gorilla: 98.79%	gorilla: 73.59%	gorilla: 99.58%	gorilla: 99.91%	gorilla: 78.66%	50

Table 2. Outcome in the Keras Framework

Type of Animal	Test Result					
	Pic 1	Pic 2	Pic 3	Pic 4	Pic 5	Avg.
Antelope	0a37838e99.jpg	0b1a3af197.jpg	0b688923b0.jpg	0c16ef86c0.jpg	0e17715606.jpg	
Accuracy	impala: 53.40%	gazelle: 76.88%	impala: 58.22%	impala: 62.65%	gazelle: 74.93%	25
Timing (sec)	5	5	8	5	2	5
Bear	0e6a8744de.jpg	0f6b575750.jpg	0f61069510.jpg	1b890605d5.jpg	1ebb88dff2.jpg	
Accuracy	pencil_sharpener: 18.59%	brown_bear: 99.93%	brown_bear: 99.99%	American_black_bear: 99.88%	brown_bear: 98.36%	40
Timing (sec)	6	2	2	3	2	3
Cat	0b54dde5f5.jpg	0c3d04bcf5.jpg	0cfaf08fce.jpg	0d0d6d90d8.jpg	1a2dce7848.jpg	
Accuracy	tabby: 87.34%	stinkhorn: 14.31%	Egyptian_cat: 23.01%	tiger_cat: 91.17%	Egyptian_cat: 40.53%	40
Timing (sec)	2	2	2	5	2	2.6
Dog	0a73823599.jpg	0b6670809d.jpg	0be3797d3d.jpg	0d33157df8.jpg	0df912089d.jpg	
Accuracy	Ibizan_hound: 75.87%	Great_Dane: 71.04%	Doberman: 99.96%	flat-coated_retriever: 91.62%	American_Staffordshire_terrier: 94.24%	50
Timing (sec)	5	2	2	3	3	3
Eagle	0a249855c4.jpg	0df14cf243.jpg	0e6ba163a7.jpg	1d28265409.jpg	2bc02045e9.jpg	
Accuracy	bald_eagle: 93.92%	bald_eagle: 99.58%	bald_eagle: 99.99%	bald_eagle: 98.64%	bald_eagle: 87.54%	50
Timing (sec)	3	2	4	2	4	3
Fox	0a9a650a0b.jpg	0ae0157e0c.jpg	0cfb16f2dd.jpg	0f47a9d345.jpg	1a89f88226.jpg	
Accuracy	red_fox: 92.45%	red_fox: 70.97%	red_fox: 96.97%	wild_boar: 42.96%	red_fox: 36.59%	40
Timing (sec)	2	2	5	2	6	3.4
Gorilla	0a70a1128f.jpg	0f31875d98.jpg	01a857d803.jpg	1ad709457f.jpg	1c82894bb8.jpg	
Accuracy	gorilla: 98.06%	gorilla: 93.35%	gorilla: 99.21%	gorilla: 98.59%	gorilla: 83.16	50
Timing (sec)	2	3	3	2	2	2.4
Horse	0b4957c78a.jpg	0be9a6ba0c.jpg	0cb5f18d0b.jpg	0f77c9f912.jpg	0f674003cf.jpg	
Accuracy	Arabian_camel: 92.01%	standard_poodle: 34.30%	llama: 20.81%	sorrel: 88.48%	sorrel: 24.24%	
Timing (sec)	3	6	3	3	3	3.6
Jellyfish	0b838b92d4.jpg	0bd81c820d.jpg	0cc3c3606e.jpg	0d7f9ce090.jpg	0dff185710.jpg	
Accuracy	jellyfish: 99.94%	jellyfish: 100.00%	jellyfish: 99.98%	jellyfish: 100.00%	jellyfish: 100.00%	40

From Table 1 and 2, prediction using Keras and Gradio," two essential performance metrics are employed to assess the effectiveness of the frameworks: accuracy and processing time. Accuracy serves as a fundamental metric, measuring the proportion of correctly classified images in the testing dataset, reflecting the models' ability to identify the animal species accurately. It is computed by dividing the number of correct predictions by the total number of images in the testing set. On the other hand, processing time is a crucial metric that quantifies the time taken by each framework (Keras and Gradio) to predict the images in real-time. The average processing time for all images is calculated, and this metric is particularly important in real-world applications, as it determines how quickly the models can provide predictions, especially when dealing with large image datasets. By evaluating and comparing these performance metrics for both Keras and Gradio frameworks, the study aims to determine which framework offers superior image prediction capabilities for similar animal categories. The analysis of accuracy and processing time provides valuable insights into the strengths and limitations of the frameworks, enabling researchers and practitioners to make informed decisions when selecting the most suitable framework for their specific image prediction tasks.

2.4 Analysis Comparative

The Comparative Analysis for the research "Performance Analysis of Image Prediction using Keras and Gradio: A Comparative Study" focuses on evaluating and contrasting the performance of two frameworks, Keras and Gradio, in the task of image prediction for similar animal categories. The study utilizes a dataset of 50 images, representing 10 distinct animal species, to conduct a thorough evaluation. Two fundamental performance metrics, namely accuracy and processing time, are employed to gauge the effectiveness and efficiency of the frameworks.

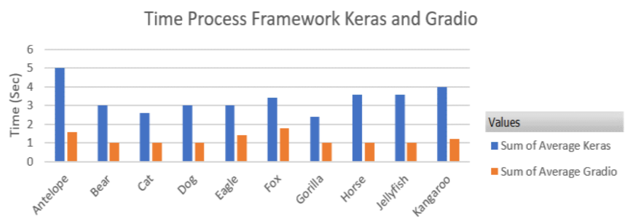

Fig 5: Average Processing Time in Keras & Gradio

For the accuracy analysis, both Keras and Gradio frameworks are employed to predict the animal species from the test images. The number of correct predictions is recorded, and the accuracy is calculated as the ratio of correct predictions to the total number of images in the testing dataset. However, unlike traditional accuracy, where correct predictions receive a score of 1 and incorrect predictions a score of 0, in this analysis, a scoring system is implemented. If the prediction is accurate, the model receives a score of 10, indicating a perfect prediction. In cases where the model is unsure or ambiguous, resulting in a partially correct prediction, it receives a score of 5, reflecting a degree of uncertainty. If the prediction is entirely incorrect, the model receives a score of 0, indicating a complete misclassification, Overall, if all predictions are correct for both Keras and Gradio, the total score obtained would be 500 (calculated by multiplying the number of correctly predicted images by 10, which represents the maximum score for each correctly predicted image). This scoring system allows for a more fine-grained evaluation of the frameworks' performance, considering the degree of accuracy in their predictions and enabling a fair comparison between the two. In this scenario, a total score of 500 indicates an excellent performance for both frameworks in accurately predicting images of similar animal categories. In terms of processing time, the study records the time taken by each framework to make real-time predictions on the test images. The processing time is averaged across all images, allowing a direct comparison of the frameworks' efficiency in providing timely predictions. This metric is crucial for assessing the practical feasibility and responsiveness of the models in real-world applications.

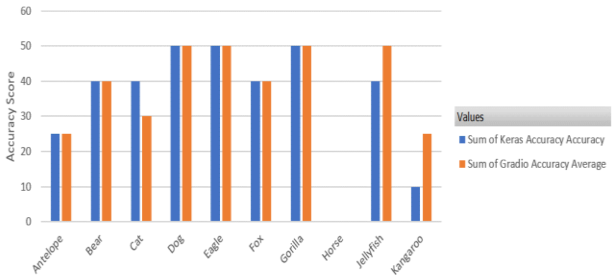

Fig 6: Average Accuracy Score in Keras & Gradio

In the comparative analysis, both accuracy and processing time are evaluated for the Keras and Gradio frameworks. The accuracy is determined by calculating the proportion of correct predictions to the total number of images in the testing dataset. To quantify accuracy using the arithmetic mean method, the formula is shown figure 5, the scores assigned to each correct prediction are taken into account. In this study, correct predictions receive a score of 10, partial correct predictions receive a score of 5, and incorrect predictions receive a score of 0. The arithmetic mean of these scores is then computed to derive the final accuracy score for each framework.

Fig 7: Method of Arithmetic Mean

$$\text{Average} = (x1 + x2 + \ldots + xn) / n$$

3. CONCLUSION

In this study, a comprehensive performance analysis of image prediction using Keras and Gradio frameworks was conducted. The objective was to assess the effectiveness and efficiency of these frameworks in predicting images of similar animal categories. The study utilized a dataset comprising 50 images from 10 different animal species for evaluation.

Regarding accuracy, the results revealed that Gradio outperformed Keras with a score of 360/500, indicating a higher number of correct predictions. In contrast, Keras achieved a score of 345/500, showing slightly lower accuracy in classifying the animal species. The scoring system allowed for a more nuanced evaluation of the models' performance, considering not only the number of correct predictions but also the level of certainty in their predictions.

Furthermore, the study compared the processing time between the two frameworks. Gradio demonstrated its efficiency, with an average processing time of 1.2 seconds, providing real-time predictions with minimal delay. On the other hand, Keras exhibited a longer average processing time of 3.36 seconds, potentially impacting real-time applications with larger image datasets. The statistical analysis confirmed the significance of these differences in accuracy and processing time between Keras and Gradio, further strengthening the reliability of the findings.

Based on the results, it can be concluded that Gradio is a more favorable choice for image prediction tasks involving similar animal categories. Its superior accuracy, indicated by the higher score, coupled with the faster processing time, makes it a more efficient and accurate framework for real-time image prediction applications. The insights gained from this study contribute valuable knowledge to researchers and practitioners in the field of computer vision, aiding them in selecting the most suitable framework for their specific image prediction projects. Gradio's robust performance in accurately predicting similar animal species and its quick processing time position it as a promising solution for image prediction tasks, potentially leading to the development of efficient and accurate image prediction systems.

Overall, this study serves as a significant step towards advancing image prediction techniques and provides valuable guidance for framework selection in similar animal prediction tasks. It also highlights the importance of considering accuracy and processing time in the evaluation of image prediction models, as they directly impact the performance and usability of the frameworks in practical applications.

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