BERZIET UNIVERSITY

FACULTY OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

ARTIFICIAL INTELLIGENCE

Project#2

Prepared by:

Name: Abdulrahman Atyani Id:1221808

Name: Khalid Hammad Id:1220857

Supervised by: Dr. Yazan Abu Farha.

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Introduction and dataset description

Animal image classification is a common and important task in computer vision, with applications in wildlife monitoring, veterinary diagnostics, agricultural systems, and educational tools. Recognizing and distinguishing between different animal species using machine learning enables the development of intelligent systems that can automate tasks such as animal identification, behavioural analysis, and habitat research. In this project, we focus on building classification models that can automatically identify animals in images, specifically three common species: cats, dogs, and snakes.

The dataset used in this project contains images from three categories: **Cats**, **Dogs**, and **Snakes**. Each image is labelled according to its animal class, and the images are stored in separate folders named after each category. The dataset consists of a diverse collection of images gathered under varying lighting, backgrounds, and poses, helping the models learn to generalize to new and unseen animal images. All images are resized to a fixed dimension (64×64 pixels) and converted into 1D feature vectors for compatibility with standard machine learning classifiers. This dataset is suitable for evaluating both simple models like Naive Bayes and Decision Trees, as well as more advanced models like Feedforward Neural Networks. The presence of three visually distinct animal classes makes this dataset ideal for testing multi-class classification performance across different algorithms.

Detailed explanation of each model

A. Naive Bayes Classifier

The Naive Bayes classifier is based on a mathematical rule called Bayes' Theorem. It predicts the class of a data point by calculating probabilities, assuming that each feature is independent of the others. While this assumption may not always be true — especially with image data — the model often performs surprisingly well.

When applied to traffic signs, each image is turned into a set of values, such as pixel brightness or colour histograms. The algorithm calculates how likely each sign class is based on these values and selects the one with the highest probability. One of the main advantages of Naive Bayes is that it is fast and requires less computational power. However, it may not work as well when features depend heavily on one another, as is often the case with images.

B. Decision Tree Classifier

A decision tree is a simple yet powerful model used in classification problems. It works by breaking down data into smaller parts using a tree-like structure, where each branch represents a decision based on one of the features. For example, when classifying traffic signs, the model might split images based on certain visual characteristics like colour or shape. Each internal node compares a feature, and the leaves of the tree represent the predicted class labels.

What makes decision trees useful is how easy they are to understand and visualize. They don't require a lot of data preparation and can handle both numerical and categorical inputs. However, they can sometimes overfit the data if the tree grows too deep, which means they might perform well on training data but poorly on new, unseen examples. Pruning techniques or setting a maximum depth can help reduce this issue.

C. Feedforward Neural Network.

A forward neural network is one of the earliest and most basic types of artificial neural networks. It's made up of layers: an input layer, one or more hidden layers, and an output layer. Information flows in one direction — from input to output — without looping back.

In traffic sign classification, an image is flattened into a one-dimensional array and passed through the network. Each layer transforms the data using weights and activation functions like ReLU or sigmoid. The output layer gives the final prediction, typically showing the likelihood for each traffic sign class. While this type of network can learn patterns in the data, it doesn't take full advantage of the spatial structure of images. More advanced models, like convolutional neural networks (CNNs), are usually better for visual tasks, but feedforward networks are still a solid choice for smaller datasets or simpler problems.

Evaluation results with basic and confusion matrices.

This section presents a comprehensive comparison of three classification models—**Naive Bayes**, **Decision Tree**, and **Feedforward Neural Network (2 layers)**—applied to the animal image classification dataset (Cats, Dogs, Snakes). Metrics used include accuracy, precision, recall, and F1-score, along with confusion matrices for performance visualization.

Classification Metrics

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Naive Bayes	0.4117	0.4164	0.4117	0.4132
Decision Tree	0.4317	0.4296	0.4317	0.4304
Feedforward Neural Network	0.5317	0.5458	0.5317	0.5178

Confusion Matrices

Each confusion matrix shows the actual class on the vertical axis and the predicted class on the horizontal axis. The values represent the number of samples.

- Naive Bayes

Actual \ Predicted	**Cat**	**Dog**	**Snake**
Cat	98	61	58
Dog	62	69	66
Snake	34	72	80

- Decision Tree

Actual \ Predicted	Cat	Dog	Snake
Cat	94	72	51
Dog	79	68	50
Snake	40	49	97

- Feedforward Neural Network

Actual \ Predicted	Cat	Dog	Snake
Cat	66	108	43
Dog	33	122	42
Snake	15	40	131

Among the three models evaluated, **the Feedforward Neural Network** demonstrated the highest overall performance, achieving better accuracy, precision, recall, and F1-score compared to Naive Bayes and Decision Tree. While **the Decision Tree** showed modest improvements, particularly in classifying the "Snake" class, it still exhibited notable misclassifications. **The Naive Bayes model** performed the weakest due to its assumption of feature independence, which is not suitable for complex image data. Although the neural network performed best, its confusion with the "Cat" class suggests further improvements could be made through data augmentation, better class balancing, or tuning the model's architecture.

Comparative Analysis and Discussion

This project compared the performance of three machine learning models—Naive Bayes, Decision Tree, and a Feedforward Neural Network—on an image classification task involving three animal classes: cats, dogs, and snakes. The models were evaluated based on accuracy, precision, recall, and F1 score**. The Naive Bayes** classifier achieved the lowest accuracy at 41.17%, which can be attributed to its assumption of feature independence—a poor fit for image data where pixel relationships carry important contextual meaning. Moreover, Naive Bayes struggles with high-dimensional input like flattened images, especially when classes have overlapping visual traits.

The Decision Tree model slightly outperformed Naive Bayes, achieving 43.17% accuracy. Its rule-based learning helped identify basic patterns, but the model appeared to overfit the training data. This could be due to limited variability in the dataset or class imbalance, where one class dominates the samples. Decision Trees are also sensitive to noise and irrelevant features, which can be problematic in image data without feature selection or dimensionality reduction.

The best results were achieved by **the Feedforward Neural Network**, with an accuracy of 53.17%. Its deeper architecture allowed it to extract more complex patterns and interactions among pixel values. However, its performance was still below optimal levels. This may be due to several factors: insufficient training data, low-quality or inconsistent image labelling, minimal data augmentation, and the relatively simple network architecture used. Neural networks generally require larger and more diverse datasets to fully generalize, and in this case, the small dataset size and possible visual similarity between classes likely limited its learning capacity. To enhance results, future work should explore data augmentation, hyperparameter tuning, and the use of convolutional layers to better handle spatial features in images.

Conclusion

This project compared the performance of three machine learning models—Naive Bayes, Decision Tree, and Feedforward Neural Network—in the task of classifying animal images into three categories: cats, dogs, and snakes. After preprocessing the images by resizing and flattening them into one-dimensional feature vectors, we trained and evaluated each model to assess their ability to learn from visual patterns and generalize to new data. The Naive Bayes classifier, though efficient and simple, delivered the lowest performance due to its unrealistic assumption of feature independence, which does not hold true in image data where pixel relationships are important. The Decision Tree model showed slight improvement by learning rule-based structures from pixel intensities, but it was still limited in capturing more abstract patterns. The Feedforward Neural Network outperformed the other two models, achieving the highest accuracy by leveraging its deeper architecture to learn complex visual features. However, its performance could further improve with more training data and tuning. This study highlights the importance of model complexity and data representation in image classification and confirms that neural networks are better suited for capturing the nuances in visual recognition tasks involving diverse animal categories.