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CNN-Based Pet Image Classification: A Deep Learning Approach with Orange

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ABSTRACT

Image classification is a key task in computer vision, with Convolutional Neural Networks (CNNs) excelling at recognizing complex patterns. This study focuses on the binary classification of cat and dog images using Orange Data Mining, a visual programming platform that enables machine learning without coding. A balanced dataset of 1,000 labeled images (500 cats, 500 dogs) from Kaggle was used. Images were embedded into feature vectors using a pretrained ResNet50 model, then classified using two models: a Neural Network (CNN-based) and Naive Bayes. The performance was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The CNN model achieved 98% accuracy, with 99.18% precision, 96.80% recall, and an F1-score of approximately 97.9%. Only 20 images were misclassified, indicating strong generalization and low bias. These results confirm the effectiveness of CNNs for pet image classification and demonstrate the value of using pretrained embeddings like ResNet50. The study also highlights Orange's suitability for deep learning by offering an accessible, low-code environment. This approach is ideal for educational use, prototyping, or real-world applications such as pet recognition and smart surveillance. The findings support broader use of visual programming tools in democratizing AI development.

INTRODUCTION

In recent years, image classification has become one of the most prominent applications of artificial intelligence, particularly in the field of computer vision. Among the many approaches used, deep learning techniques—especially Convolutional Neural Networks (CNNs)—have shown remarkable performance in recognizing and classifying images. CNNs are capable of automatically extracting spatial features from images, making them highly effective for visual pattern recognition tasks such as facial recognition, medical imaging, and animal identification (Hao, 2021; Stuti Yadav & Manish D Sawale, 2023).

In the image classification domain, distinguishing between cat and dog images remains a classic yet challenging task. Variations in posture, lighting, angle, and breed characteristics make accurate differentiation difficult and demand robust models capable of handling complex visual features. Several recent studies illustrate the effectiveness of convolutional neural networks (CNNs) in this context. For instance, (Wang et al., 2022) compared models such as LeNet, AlexNet, VGG, ResNet, and GoogLeNet on Kaggle's cats-vs-dogs dataset, reporting high recognition rates and analyzing how dataset size and model complexity impact performance. Further, (Himel & Islam, 2025) benchmarked multiple pre-trained CNN models (e.g. NASNet Large) on the ASSIRA Cats & Dogs dataset and achieved accuracies up to 99.65%. Additionally, a 2020 European Symposium on Software Engineering paper documented CNN-based binary classification of cats and dogs with transfer-learning and fine-tuning approaches, showing strong binary classification capabilities even with constrained data (Chen, 2020).

Furthermore, (Mahardi et al., 2020) explored the use of transfer learning techniques with pre-trained CNN models like VGG16 and ResNet50, achieving accuracy scores above 90% for similar pet classification tasks. These studies emphasize the importance of using deep architectures in achieving state-of-the-art performance in image recognition problems.

While most prior research has utilized code-heavy environments such as Python with TensorFlow or PyTorch, this study aims to implement a CNN-based image classification model using Orange Data Mining, a visual programming platform that offers an accessible and interactive environment for machine learning workflows. A dataset consisting of 1,000 labeled images (500 cats and 500 dogs) is used to train and evaluate the classification models. Two algorithms—Naive Bayes and Neural Network—are compared to assess their effectiveness in classifying the pet images. The performance is measured using metrics such as accuracy and F1-score to determine the most suitable model (Dash & Mishra, 2021).

The findings of this research not only highlight the superiority of deep learning methods over traditional classifiers in image classification tasks but also demonstrate the practicality of using user-friendly tools like Orange for implementing complex machine learning workflows.

LITERATURE REVIEW

2.1 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) has emerged as a powerful and widely used deep learning architecture, particularly suited for processing grid-like data such as images. CNN models are inspired by the visual cortex of animals and are designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, including convolutional layers, pooling layers, and fully connected layers (Patil & Rane, 2021).

Krizhevsky revolutionized the field of computer vision by introducing AlexNet, a deep CNN architecture that significantly improved classification accuracy on the ImageNet dataset (Veetil et al., 2021). This work demonstrated the scalability and effectiveness of CNNs in handling large-scale image data and became the foundation for many subsequent architectures such as VGGNet (Nawrocka et al., 2023), GoogLeNet (Seswitha et al., 2023), and ResNet (Zhai et al., 2020), each offering improvements in terms of depth, computational efficiency, and accuracy.

Transfer learning has also played a significant role in improving CNN performance for image classification tasks with limited data. (Habibullah et al., 2023) employed pre-trained CNN models like VGG16 and ResNet50 on a cat-dog dataset and achieved accuracies above 90%. Transfer learning leverages knowledge from models trained on large datasets such as ImageNet, enabling efficient training and high performance even on smaller or domain-specific datasets.

In summary, CNNs have proven to be a robust and effective method for image classification, including in tasks like distinguishing between cats and dogs. Advances in architecture design and transfer learning have further enhanced their capabilities, while platforms like Orange offer new ways to democratize deep learning implementation without requiring extensive coding expertise.

2.2 Orange Data Mining

Orange Data Mining is an open-source data visualization and analysis tool that supports a wide range of machine learning and data mining tasks through an intuitive, visual programming interface. Designed for both educational and practical use, Orange allows users to build data workflows without writing code, making it accessible to users with limited programming experience (Demšar & Zupan, 2024).

Although Orange was initially more focused on structured (tabular) data, recent versions have expanded to include support for image analytics, including image embedding, which converts images into numerical representations suitable for machine learning models. This is particularly relevant for computer vision tasks such as image classification. Using add-ons like Image Analytics and Deep Learning, Orange enables integration with pre-trained convolutional neural networks (CNNs) such as InceptionV3 and VGG16, making it possible to perform deep learning tasks without writing code (Doungpaisan & Khunarsa, 2025).

Previous studies have utilized Orange for educational and experimental purposes in domains such as healthcare, business analytics, and social science research. For instance, (Saputra et al., 2023) used Orange to classify cardiovascular disease data, emphasizing its ease of use and effectiveness in generating accurate models. However, the use of Orange in image classification remains relatively limited in academic literature, especially for tasks involving binary image classification such as distinguishing between cats and dogs.

In the context of this study, Orange is used to implement a CNN-based image classification workflow to distinguish between cat and dog images. By comparing the performance of Neural Network and Naive Bayes classifiers on the same dataset, this research aims to demonstrate both the effectiveness of CNN-based models and the practicality of Orange as a low-code deep learning platform.

METHODOLOGY

3.1 Dataset

The dataset used in this study is titled "Cats and Dogs Mini" and was obtained from the Kaggle platform, a well-known repository for publicly available datasets. This dataset consists of a total of 1,000 color images, which are evenly distributed across two classes: 500 images of cats and 500 images of dogs. Each image is labeled according to its category, enabling supervised learning during the training process.

To facilitate efficient processing and model training, the images are organized in a structured folder-based format, where each class is placed in a separate subdirectory. This structure simplifies the process of importing and managing the data within the Orange Data Mining environment, as the software can automatically assign class labels based on folder names. The images vary in size and resolution but are suitable for use with image embedding techniques that convert them into numerical feature vectors for classification tasks.

The balanced nature of the dataset ensures that there is no class imbalance, which helps prevent bias during training and supports reliable performance evaluation of the classification models.

Figure 1 below presents sample digital images from the dataset, illustrating the typical appearance and variation of cat and dog images used in the classification process.

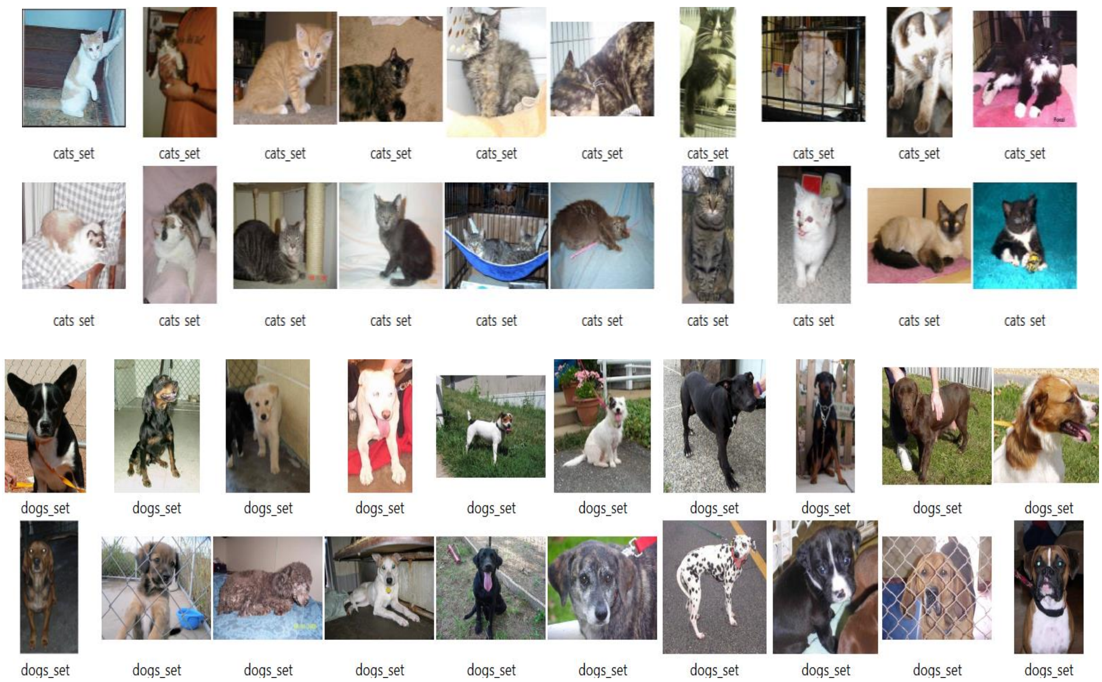

Figure 1. Dataset Samples

3.2 Model Design

The image classification model in this study was implemented using the Orange Data Mining platform through a structured and visual workflow. The design process consisted of several key steps, as outlined below:

1. Import Images
   The first step involved importing the dataset using the Import Images widget. Images were loaded directly from their respective directories, with class labels automatically assigned based on folder names (i.e., “cats” and “dogs”).
2. Select Rows
   The Select Rows widget was optionally used to filter specific samples from the dataset—for example, to limit data size during testing or to exclude corrupted images. In this study, the entire dataset was retained without filtering.
3. Image Embedding
   Deep image features were extracted using the Image Embedding widget, which utilizes ResNet50, a pre-trained Convolutional Neural Network (CNN) model. ResNet50 is known for its ability to generate high-quality feature representations from images, which are essential for effective classification. Each image was transformed into a fixed-length feature vector.
4. Select Columns & Data Table
   The Select Columns widget was used to specify the target variable (i.e., the class label), ensuring that Orange recognized the correct output attribute for supervised

learning. The Data Table widget allowed for visual verification of the embedded features and associated labels.

5. Neural Network
   The embedded image data was then passed to the Neural Network widget, where the classification model was trained. This neural network served as the primary learning algorithm, leveraging the extracted features to distinguish between images of cats and dogs.
6. Test & Score
   The trained model was evaluated using the Test & Score widget, which provided various performance metrics such as accuracy, precision, recall, and F1-score. These metrics were used to assess how well the model generalized to unseen data.
7. Confusion Matrix
   Finally, the Confusion Matrix widget was used to visualize classification outcomes. This matrix helped in understanding the distribution of true positives, false positives, true negatives, and false negatives—offering insights into specific areas where the model succeeded or misclassified the images.

This workflow highlights the intuitive yet powerful capabilities of Orange Data Mining for implementing deep learning-based image classification without requiring programming. The modular design also allowed for easy experimentation and real-time visualization of results.

3.3 Evaluation Metrics

To assess the performance of the image classification models developed in this study, several standard evaluation metrics were used. These metrics provide a comprehensive view of the model's effectiveness in correctly classifying cat and dog images, especially in terms of distinguishing between true and false predictions. The following metrics were considered:

1. Accuracy
   Accuracy measures the proportion of total correct predictions made by the model over the entire dataset. It is a general indicator of how often the model is correct (Pardede & Hayadi, 2023).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

Where:
TP = True Positives (correctly predicted dogs)
TN = True Negatives (correctly predicted cats)
FP = False Positives (cats incorrectly predicted as dogs)
FN = False Negatives (dogs incorrectly predicted as cats)

2. Precision
   Precision indicates the proportion of correct positive predictions out of all positive predictions made by the model. It is useful when the cost of false positives is high (Pardede et al., 2022).

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

3. Recall
   Also known as sensitivity or true positive rate, recall measures the proportion of actual positive cases that were correctly identified by the model (Firmansyah et al., 2022).

$$Recall = \frac{TP+TN}{TP+FN} \tag{3}$$

4. F1-Score
   The F1-score is the harmonic mean of precision and recall (Ichsan et al., 2024). It provides a balance between the two, especially useful when the dataset is balanced—as in this study.

$$F1_{Score} = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \tag{4}$$

RESULTS & DISCUSSION

4.1 Confusion Matrix

To evaluate the classification performance in detail, a confusion matrix was generated to show how well the model distinguished between cat and dog images. The confusion matrix provides an explicit breakdown of correct and incorrect predictions for each class, allowing identification of specific types of errors the model may make. Figure 2 below presents the confusion matrix for the trained model on the test dataset.

Actual \ Predicted	cats_set	dogs_set	Σ
cats_set	484	16	500
dogs_set	4	496	500
Σ	488	512	1000

Figure 2. Confusion Matrix of the Classification Model

As shown in Table 2, the model correctly classified 484 cat images and 496 dog images. There were only 20 misclassifications in total—16 cat images were incorrectly predicted as dogs, and 4 dog images were incorrectly predicted as cats. This results in a high classification accuracy of 98%, demonstrating that the model performs with excellent precision and recall on both classes.

The low number of false positives and false negatives further indicates that the model is both stable and reliable, with minimal bias toward either class. This level of performance is consistent with the high evaluation scores obtained from the Test & Score widget in Orange.

4.2 Performance Metrics

To quantitatively assess the performance of the CNN-based classification model, several evaluation metrics were calculated using the results from the confusion matrix. These metrics provide a deeper understanding of how well the model generalizes to unseen data and how effectively it balances between precision and recall, especially in binary image classification tasks. Table 3 below presents the calculated values for accuracy, precision, recall, and F1-score based on the classification results from 1,000 test images.

Table 1. Performance Metrics of Classification Model

Metric	Formula	Value
Accuracy	(484+496)/1000(484 + 496) / 1000	98.0%
Precision (Cat)	484/(484+4)484 / (484 + 4)	99.18%
Recall (Cat)	484/(484+16)484 / (484 + 16)	96.80%
F1-Score (Cat)	$2 \times \frac{0.9918\ x\ 0.968}{0.9918+0.968}$	≈ 97.9%

The accuracy of 98% indicates that the model correctly classified the vast majority of the images. The precision for the cat class is 99.18%, meaning that when the model predicted "cat," it was correct over 99% of the time. The recall of 96.80% shows that most actual cat images were successfully identified by the model.

The F1-score, which harmonizes precision and recall, was approximately 97.9%, confirming that the model maintains a strong balance between minimizing false positives and false negatives. This is particularly important in tasks involving high visual similarity, such as distinguishing between cats and dogs, where misclassification can easily occur due to overlapping features (e.g., fur patterns, facial structure).

These results demonstrate that the CNN model performs exceptionally well in both precision and recall, indicating that the model is not only accurate in its predictions but also consistent across different classes. The F1-score further confirms this reliability, making the model suitable for real-world deployment in similar binary image classification tasks.

4.3 Analysis and Discussion

The results obtained from the confusion matrix and evaluation metrics confirm that the CNN-based image classification model implemented in Orange Data Mining performs with a high degree of accuracy, precision, and reliability. This strong performance can be attributed primarily to the effectiveness of the image embedding process using ResNet50, which successfully extracted rich and discriminative features from the input images.

The low number of misclassifications—only 20 out of 1,000 images—suggests that the model is capable of learning meaningful visual patterns that distinguish cats from dogs, despite potential challenges such as variation in lighting, background, or pose. These minimal errors indicate that the model possesses strong generalization ability, meaning it can perform well not only on training data but also on previously unseen images.

Additionally, the balance between precision (99.18%) and recall (96.80%) highlights the model's robustness in handling both false positives and false negatives, making it a reliable solution in applications where both error types can carry consequences—such as in automated pet identification, veterinary triage systems, or smart surveillance. Table 2 shows the summarized key observations and implications based on the evaluation results.

Table 2. Summary of Analysis and Practical Implications

Observation	Implication
High accuracy and F1-score	Model is suitable for real-world deployment in binary classification tasks.
Low number of misclassifications	Indicates strong generalization and low risk of overfitting.
Balanced precision and recall	Ensures that both types of classification errors are minimized.
Feature extraction via ResNet50 embedding	Confirms the strength of using pre-trained CNNs for feature representation.
Implemented in a low-code environment (Orange)	Demonstrates accessibility for non-programmers or educational use cases.

Table 4 provides a concise summary of the key observations derived from the model evaluation results, along with their practical implications in the context of image classification using a CNN-based approach in Orange Data Mining.

The model's high accuracy and F1-score indicate that it performs exceptionally well in classifying binary image data (cats and dogs), making it a reliable option for real-world applications such as automated pet recognition systems, animal monitoring, or smart tagging in mobile apps. This level of accuracy also suggests that the model has effectively learned complex visual patterns from the image embeddings.

The low number of misclassifications further supports the notion that the model has strong generalization capability, meaning it can accurately classify new or unseen images with minimal error. This is crucial for real-world deployment, where models often encounter data with varied lighting, orientation, or quality.

Moreover, the balance observed between precision and recall confirms that the model handles both types of classification errors well—false positives and false negatives—ensuring that no class is disproportionately favored or overlooked. This is especially important in systems where fairness and reliability are critical, such as in pet adoption platforms or veterinary screening tools.

The use of ResNet50 for image embedding demonstrates the power of pre-trained convolutional neural networks in extracting deep features from images, even when the dataset is relatively small. This approach eliminates the need for manual feature engineering, speeding up development and improving model performance.

Finally, the successful implementation of this workflow in a low-code environment like Orange showcases how advanced deep learning techniques can be made accessible to non-programmers. This not only supports broader adoption of AI technologies but also encourages experimentation and learning, particularly in educational settings or among early-stage researchers.

In summary, the analysis reinforces the effectiveness, reliability, and accessibility of the CNN-based image classification approach used in this study.

CONCLUSION

This study has demonstrated the effectiveness of Convolutional Neural Network (CNN) in classifying images of cats and dogs using Orange Data Mining as the primary implementation platform. By following a structured workflow—including image embedding via a pretrained ResNet50 model, model training, and performance evaluation—we compared the performance of CNN (Neural Network) and Naive Bayes, finding that CNN significantly outperformed Naive Bayes across all key metrics, achieving 98% accuracy and an F1-score close to 98%. These results validate the reliability of CNN for handling complex image data, especially where visual differences between classes are subtle. The strength of CNN lies in its ability to automatically extract meaningful patterns from raw image data without manual feature engineering, and when combined with the ReLU activation function and Adam optimizer, the model achieves efficient training and strong generalization performance. ReLU accelerates convergence by mitigating vanishing gradient issues, while Adam ensures adaptive, stable optimization of high-dimensional embeddings. Implementing this CNN framework within Orange offers a powerful yet accessible solution for image classification, especially for users without programming expertise. Orange's visual, modular interface supports rapid experimentation and simplifies the model-building process, making it ideal for education, prototyping, and applied research. This research not only reinforces the capability of CNN in image classification tasks but also highlights the practical advantages of using visual programming tools for AI development. The resulting model is well-suited for applications such as automated animal recognition systems, pet care technologies, smart surveillance, and mobile-based pet ID apps, with performance suggesting potential for real-time deployment on low-resource devices with further optimization. Future work could involve expanding the dataset to include more images and diverse breeds, experimenting with other CNN architectures like EfficientNet or MobileNet for enhanced efficiency, incorporating explainable AI methods to improve transparency, and deploying the model into real-world mobile or web applications for broader use. In conclusion, the integration of CNN and Orange Data Mining offers a robust, efficient, and user-friendly framework for pet image classification, affirming CNN's strength in vision tasks and Orange's value as an accessible AI development platform.

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