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Convolutional Neural Network (CNN) Model for Multi-Category Classification of Animals

Mohammad Iqbal Bachtiar[1*], Rachmad Hidayat[2], Rizki Anantama[3], Mohammad Ilham Bahri[4], Zeinor Rahman[5]

[1]Informatics, University of Bahaudin Mudhary Madura, Sumenep, 69471, Indonesia.
[2]Industial Engineering, University of Trunojoyo Madura, Bangkalan, 69162, Indonesia.
[3]Information System, University of Bahaudin Mudhary Madura, Sumenep, 69471, Indonesia.
[4]Information System, University of Bahaudin Mudhary Madura, Sumenep, 69471, Indonesia.
[5]Informatics, University of Bahaudin Mudhary Madura, Sumenep, 69471, Indonesia

Correspondence:
Mohammad Iqbal Bachtiar, Informatics, University of Bahaudin Mudhary Madura, Sumenep, 69471, Indonesia.
Email:
iqbalbachtiar@unibamadura.ac.id

Abstract
The progress in artificial intelligence (AI) technology has led to substantial transformations in several areas, particularly in image recognition and classification. Convolutional neural networks (CNNs) are widely recognized as powerful methods in the field of digital image processing, particularly for tasks involving pattern recognition and image classification. CNNs extract essential features from images through convolution and pooling operations, followed by fully connected layers that produce classification output. This research aims to train a CNN model to classify animal images into categories such as cats, rabbits, cows, chickens and others. Image classification is crucial for practical applications, including image database management, visual search, and automated recognition systems. Using a labeled dataset, the CNN model is trained to recognize and classify images based on distinctive visual features characteristic of each category. The training process involves data preprocessing, network architecture implementation, and hyperparameter optimization. Model performance is evaluated using metrics like accuracy, precision, recall, and F1-score to ensure accurate and reliable classification results. Result concludes that CNN is a highly effective approach for classifying animal images, achieving a loss rate of 0.1949 and an accuracy of 95.45%.

Keywords: Convolutional Neural Network, Image Classification, Animal Recognition, Deep Learning, Model Evaluation Metric.

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Introduction

The progress in artificial intelligence (AI) technology has led to substantial transformations in several areas, particularly in image recognition and classification. Utilizing convolutional neural networks (CNN) stands out as one of the most efficient methods in digital image processing (Lecun et al., 1998). CNN is a type of neural network architecture specifically created to handle grid-structured data, such as images, and has proven to be superior in various tasks involving pattern recognition and image classification (Scott et al., 2022).

CNN functions by extracting key features from images through a sequence of convolution and pooling operations, this is followed by fully connected layers that generate the classification output. The strength of CNNs is their capability to autonomously learn and identify intricate patterns within images, eliminating the necessity for complex manual feature extraction. This capability makes CNN a top choice for various applications, from facial recognition and object detection to image classification (Kong et al., 2019).

This research aims to train a CNN model to classify animal pictures into several categories, such as cat, rabbit, cow, chicken and others. Image classification is a crucial task in many practical applications, including image database management, visual search, and automated recognition systems. Using a labeled image dataset, the CNN model will be trained to recognize and classify images based on distinctive visual features characteristic of each category (Divya Meena & Agilandeeswari, 2019).

The training process of a CNN model involves several stages, starting from data preprocessing, such as image normalization and augmentation, to the implementation of the network architecture and hyperparameter optimization (Pravin et al., 2023). Moreover, model performance is assessed using metrics such as accuracy, precision, recall, and F1-score to ensure the model delivers accurate and reliable classification results.

This research aims to develop a CNN model that can achieve precise image classification with high accuracy, providing further insights into the effectiveness and efficiency of CNN in image recognition and classification tasks. The findings of this study can be utilized across multiple sectors including security, healthcare, transportation, and creative industries, all of which demand rapid and precise image recognition technology.

Literature Review

1. *Convolutional Neural Networks* (CNN)

CNN have become one of the most powerful tools in image recognition and classification (Natarajan et al., 2023). CNN have been utilized across diverse domains, such as facial recognition, object detection, and image classification. This research reviews the literature related to training CNN models to classify animal images into several categories, such as cats, rabbits, cows, chickens, and others (Norouzzadeh et al., 2018).

2. *Convolution and Pooling in CNN*

CNNs utilize convolution operations to extract important features from images. In their paper introducing AlexNet, (Krizhevsky et al., 2017) demonstrated that the first convolutional layer acts as an edge detector, while deeper layers identify more complex features. Pooling, usually max-pooling, is employed to decrease the dimensionality of features, aiding in the reduction of overfitting and improvement of computational efficiency (Humayun et al., 2022).

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3. Network Architecture

Since AlexNet (Mittal et al., 2023), various CNN architectures have been developed to enhance accuracy and efficiency. VGGNet proposed the use of small (3x3) convolutional layers repeatedly to deepen the network. Meanwhile, GoogLeNet introduced the Inception module, which allows for the parallel use of filters of different sizes (Prasetyo, 2022). ResNet introduced skip connections to address the issue of vanishing gradients, allowing the training of extremely deep networks (Martija et al., 2020).

4. Training Dataset

The success of CNN models heavily relies on the dataset used for training. Large datasets like ImageNet have become the standard for training and testing CNN models (Rabah, 2021). For this research, a combination of existing datasets covering more than three animals based on the previous ones can be utilized.

5. Data Augmentation Techniques

Data augmentation is a method employed to enlarge and diversify training datasets without the need for additional data collection. Methods such as rotation, cropping, adjusting brightness, and flipping are utilized to enhance the robustness of models against variations in images. Show that data augmentation can greatly improve CNN model performance by decreasing overfitting (Shorten & Khoshgoftaar, 2019).

6. Optimization and Training

During the training of CNN models, parameters are optimized using methods such as stochastic gradient descent (SGD) and more recent variations like Adam (Kingma & Ba, 2017). Research by (Wilson et al., 2017) compared different optimization algorithms and concluded that the selection of algorithms has a notable effect on both the convergence and ultimate performance of the model.

7. Performance Evaluation Model

CNN model performance is assessed using metrics like accuracy, precision, recall, and F1-score. Furthermore, a confusion matrix is employed to provide a detailed view of classification errors. Research by (Tharwat, 2021), provides a comprehensive guide on the interpretation and usage of evaluation metrics in the context of classification.

8. CNN Applications in Image Classification

The application of CNNs in image classification spans various domains. In the field of biology, CNNs have been used to classify plant species based on leaf images (Abady et al., 2024). In the automotive industry, CNNs are utilized to recognize vehicle types and models from road images (Lee et al., 2018). The use of CNNs in animal classification has been researched by (Norouzzadeh et al., 2018), demonstrating high performance in recognizing animal species from wildlife images.

Research Methods

1. Data Collection

The data for this study will be sourced from publicly available categorized image datasets. These datasets include ImageNet, a vast collection with millions of images organized into

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thousands of classes and also encompass small images (32x32 pixels) from diverse categories. Additionally, Kaggle datasets will be used, specifically those available on the platform for plant images.

Collect data representative of the animals to be collected. This data can be numeric features based on the symptoms being examined such as body size, weight, tail length, colour, or even features extracted from animal images using methods such as Convolutional Neural Networks (CNN).

Images will be collected from the aforementioned datasets and organized into main categories: cat, rabbit, cow, chicken and others. Each category will contain at least 872 images to ensure diversity and balance in the data.

1	AnimalName	symptoms1	symptoms2	symptoms3	symptoms4	symptoms5	Dangerous
2	Dog	Fever	Diarrhea	Vomiting	Weight loss	Dehydration	Yes
3	Dog	Fever	Diarrhea	Coughing	Tiredness	Pains	Yes
4	Dog	Fever	Diarrhea	Coughing	Vomiting	Anorexia	Yes
5	Dog	Fever	Difficulty breathing	Coughing	Lethargy	Sneezing	Yes
6	Dog	Fever	Diarrhea	Coughing	Lethargy	Blue Eye	Yes
67	cat	Fatty stool	Diarrhea	Vomiting	Weight loss	Pain	Yes
68	cat	Nausea	Loss of appetite	Vomiting	Firm	Distended stomach	Yes
69	cat	Fever	Swelling in the bite area	Lethargy	Limp	Pain	Yes
70	cat	Fever	Loss of appetite	Eyeproblem	Liver disease	Nuerological	Yes
71	cat	Fever	Mild sneezing	Coughing	Nasal	Ocular discharge	Yes
78	Rabbit	Immediate death	Difficulty in breathing	Blue colored lip	Bloody discharge	Neurologic abnormalities	Yes
79	Rabbit	Fever	Pox lession on skin	Skin reashes	Nasal discharge	Mortality varies	Yes
80	Rabbit	Red on affected area	Horny growth	Wart-like growth	Red skin	Lesions on ear	Yes
81	Rabbit	Fever	Chills	Skin ulcer	Exhaustion	Swollen and painfull	Yes
82	Rabbit	Watering Diarrhea	Depression	Emaciation	Ruffled Coat	Lethargy	Yes
83	cow	loss in weight	emaciation	loss of appetite	Weakness	diarrhoea	Yes
84	chicken	loss of appetite	diarrhea	swollen purple wattle	Swollen comb	Lameness	Yes
85	chicken	loss of appetite	diarrhea	ruffled feathers	Weight loss	Inability to absorb nutrients	Yes
86	chicken	egg production decreases	stunted growth	Blindness	Distinctive bumps	Facial swelling	Yes
87	chicken	loss of appetite	thirst	ruffled feathers	Closed eyes	Diarrhea	Yes
88	cow	Fever	weakened legs	los of the ability to walk	Mammary glads	Fluif filled blisters	Yes
89	cow	Fever	weakened legs	los of the ability to walk	Weight loss	Lameness	Yes
90	cattle	abortion at the end of gestation	Fatigue	weak calves	Join pains	Swelling of internal organs	Yes

Figure 1. Data Collection

2. Data Preprocessing

Missing data is managed through imputation or deletion methods, depending on the characteristics of the dataset. Imputation is done by replacing missing values using the median or mean of the respective columns. Deletion is applied if the amount of missing data is insignificant or if imputation is not possible. After that, removing Irrelevant Columns such as "animal_name" containing unimportant string data is removed to ensure efficient data clustering. Removing unnecessary columns is an important step in preprocessing to improve the accuracy of clustering results. Then, Data is normalized to ensure that each attribute has the same scale, so that no attribute dominates the clustering. Normalization is done with Min-Max Scale or Z-score. Some attributes are transformed to improve data distribution or reduce skewness, such as by using log transform or square root transform.

Including Images will be inspected to ensure they match the predefined categories. Blurry, damaged, or miscategorized images will be removed. Subsequently, the data will undergo normalization by scaling their pixel values to the range [0, 1], achieved by dividing the pixel values by 255. Augmentation techniques like rotation, flipping, zooming, and brightness adjustment will be utilized to increase the variety of training data and mitigate overfitting.

3. CNN Architecture

Convolutional Neural Network (CNN) is a deep learning model tailored for processing structured grid data, such as images. CNNs excel in tasks like image classification, object

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detection, and various computer vision applications. The typical CNN architecture includes the following layers:

- Input Layer: This layer stores the original pixel values of the input image. In the case of a colour image, it typically consists of three channels corresponding to the RGB colour model.
- Convolutional Layers: These layers use a series of filters (kernels) on the input image. The filters move across the image, performing convolution operations to generate feature maps. These feature maps assist in identifying elements like edges, textures, and patterns within the image. The convolution operation is defined by equation (1).

$$(I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n) \qquad (1)$$

I = Input matrix (for example, image).
K = Kernel or filter, which is a small matrix used to detect certain features.
i, j = Coordinates of the output element.
m, n = Index used to explore elements of the kernel.
$\sum_m \sum_n$ = The addition operation is performed on all kernel elements.
$I(i+m, j+n)$ = The pixel value of the input at the position offset by m and n.
$K(m,n)$ = The value of the kernel element at position m, n.

- Activation Function (ReLU): The Rectified Linear Unit (ReLU) activation function is employed to incorporate non-linear properties into the model, improving its capacity to capture complex patterns effectively, while ensuring originality. ReLU is defined as equation (2).

$$f(x) = \max(0, x) \qquad (2)$$

x = Input value provided to the activation function.
$f(x)$ = Resulting value from the ReLU activation function.

- Pooling Layers: These layers reduce the spatial dimensions (width and height) of the feature maps while retaining essential information and reducing computational complexity, thereby avoiding plagiarism. The most typical type is Max Pooling, where the maximum value within a set of values in the feature map is selected.
- Fully Connected (Dense) Layers: following multiple convolutional and pooling layers, the output is flattened into a one-dimensional vector and then processed through one or more fully connected layers. These layers are employed to conduct classification using the features extracted by the convolutional layers.
- Output Layer: This layer generates the final predictions, usually employing a softmax activation function for multi-class classification tasks. The softmax function transforms the output scores into probabilities, show as equation (3).

$$softmax(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (3)$$

z_i = Input score from class to-i.
e^{z_i} = Exponentiality of the input score.
$\sum_j e^{z_j}$ = The summation of all exponential input scores for all classes j.

4. Visualization Data

In the context of a 3 dimensional visualization, three attributes from the animal dataset (for example, weight, body size, and tail length) are assigned to the X, Y, and Z axes, respectively. Each point within the 3D space represents an individual animal. Subsequently, the animals are categorized into distinct clusters, with each cluster visualized using a different color to enhance differentiation. Furthermore, the centroid of each cluster is illustrated as an enlarged point or marker positioned at the center of the respective cluster (Yuni K, K. C., Hidayat, N., & Musfiroh, A., 2025)..

5. Performance Evaluation

The model's performance will be assessed using defined metrics such as Accuracy, Precision, Recall, and F1-Score. Accuracy represents the ratio of correct predictions to total predictions. Precision, Recall, and F1-Score will be utilized to evaluate the model's performance across each category. The trained model will be tested using testing data to evaluate its actual performance beyond the training data (Rahman, H., Abidin, R. Z., & Hidayat, N., 2025).

Results and Discussion

1. Classification Report

This study reveals the results of implementing a transfer learning-based image classification system to distinguish various animal species into appropriate categories. Through the use of separate test datasets, our model achieved an average accuracy of 95%, demonstrating robust capability in recognizing unique characteristics of each species. This can be observed in Figure 1.

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.92	0.96	25
1	0.90	1.00	0.95	19
accuracy			0.95	44
macro avg	0.95	0.96	0.95	44
weighted avg	0.96	0.95	0.95	44

Figure 1. Classification Report Results

2. Model Training and Validation Results

Throughout training, the CNN model underwent 50 epochs using a batch size of 32. The training results are shown in Figures 2. It was found that the loss value was minimal, with an

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accuracy of. The chart below shows the evolution of accuracy and loss on both training and validation data throughout the training process.

```
Epoch 47/50
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 163ms/step - accuracy: 1.0000 - loss: 0.0023 - val_accuracy: 0.9545 - val_loss: 0.1922
Epoch 48/50
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 171ms/step - accuracy: 1.0000 - loss: 0.0028 - val_accuracy: 0.9545 - val_loss: 0.1928
Epoch 49/50
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 159ms/step - accuracy: 1.0000 - loss: 0.0024 - val_accuracy: 0.9545 - val_loss: 0.1941
Epoch 50/50
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 163ms/step - accuracy: 1.0000 - loss: 0.0026 - val_accuracy: 0.9545 - val_loss: 0.1949
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - accuracy: 0.9489 - loss: 0.2190
Loss: 0.1949, Accuracy: 0.9545
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 341ms/step
```

Figure 2. Training Results 50 epochs

Next, the model was trained to classify animal images into several categories. The model training ran for 50 training epochs. The training results are shown in Figure 3. It was found that the minimal loss value was 0,1949, with an accuracy of 95,45%.

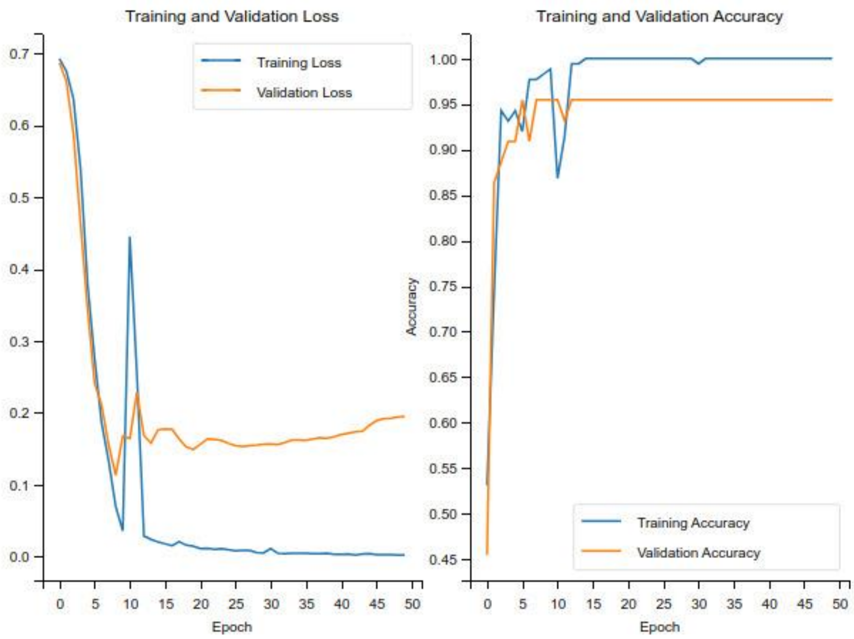

Figure 3. Graph of Loss and Accuracy Values Against Training and Validation Epochs

Conclusions and Practical Implication

Conclusion

This study demonstrates that CNN is a highly effective approach in addressing the classification of animal images. With a loss rate of 0.1949, CNN significantly reduces errors in predicting animal categories, showcasing its ability to comprehend and utilize crucial features from images. An accuracy of 95.45% confirms that this model excels in identifying and classifying different animals.

These findings not only validate the reliability of CNN in image classification tasks but also highlight its potential applications in various contexts, including livestock monitoring, wildlife conservation, and image recognition technologies. Nevertheless, challenges remain, such as adapting to variations in poses, lighting conditions, and diverse backgrounds in images.

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References

Abady, aglaa F. E., Zayed, H. H., & Taha, M. (2024). Source printer identification using convolutional neural network and transfer learning approach. IAES International Journal of Artificial Intelligence (IJ-AI), 13(1), Article 1. https://doi.org/DOI: 10.11591/ijai.v13.i1.pp948-960

Divya Meena, S., & Agilandeeswari, L. (2019). An Efficient Framework for Animal Breeds Classification Using Semi-Supervised Learning and Multi-Part Convolutional Neural Network (MP-CNN). IEEE Access, 7, 151783–151802. https://doi.org/10.1109/ACCESS.2019.2947717

Humayun, M., Sujatha, R., Almuayqil, S. N., & Jhanjhi, N. Z. (2022). A Transfer Learning Approach with a Convolutional Neural Network for the Classification of Lung Carcinoma. Healthcare, 10(6), Article 6. https://doi.org/10.3390/healthcare10061058

Kingma, D. P., & Ba, J. (2017). Adam: A Method for Stochastic Optimization (No. arXiv:1412.6980; Issue arXiv:1412.6980). arXiv. http://arxiv.org/abs/1412.6980

Kong, B., Supančič, J., Ramanan, D., & Fowlkes, C. C. (2019). Cross-Domain Image Matching with Deep Feature Maps. International Journal of Computer Vision, 127(11–12), Article 11–12. https://doi.org/10.1007/s11263-018-01143-3

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), Article 6. https://doi.org/10.1145/3065386

Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), Article 11. https://doi.org/10.1109/5.726791

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manufacturing Letters, 18, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002

Martija, M. A. M., Dumbrique, J. I. S., & Naval, P. C., Jr. (2020). Underwater Gesture Recognition Using Classical Computer Vision and Deep Learning Techniques. Journal of Image and Graphics, 8(1), Article 1. https://doi.org/10.18178/joig.8.1.9-14

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DOI:

Mittal, S., Srivastava, S., & Jayanth, J. P. (2023). A Survey of Deep Learning Techniques for Underwater Image Classification. IEEE Transactions on Neural Networks and Learning Systems, 34(10), Article 10. https://doi.org/10.1109/TNNLS.2022.3143887

Natarajan, B., Elakkiya, R., Bhuvaneswari, R., Saleem, K., Chaudhary, D., & Samsudeen, S. H. (2023). Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Networks. IEEE Access, 11, 67308–67321. https://doi.org/10.1109/ACCESS.2023.3289586

Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. Proceedings of the National Academy of Sciences, 115(25), Article 25. https://doi.org/10.1073/pnas.1719367115

Prasetyo, E. (2022). Multi-level residual network VGGNet for fish species classification. Computer and Information Sciences.

Pravin, S. C., Rohith, G., Kiruthika, V., Manikandan, E., Methelesh, S., & Manoj, A. (2023). Underwater Animal Identification and Classification Using a Hybrid Classical-Quantum Algorithm. IEEE Access, 11, 141902–141914. https://doi.org/10.1109/ACCESS.2023.3343120

Rabah, C. B. (2021). Automatic source scanner identification using 1D convolutional neural network. Multimedia Tools and Applications.

Rahman, H., Abidin, R. Z., & Hidayat, N. (2025). Analysis Of The Economic Potential Of The Marine Capture Fisheries Sector In Sumenep Regency With Gordon-Schaefer Model Approach. *IOP Conference Series: Earth And Environmental Science*, 012038.

Scott, A. C., Solórzano, J. R., Moyer, J. D., & Hughes, B. B. (2022). The Future of Artificial Intelligence. International Journal of Artificial Intelligence and Machine Learning, 2(1), Article 1. https://doi.org/10.51483/IJAIML.2.1.2022.1-37

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on Image Data Augmentation for Deep Learning. Journal of Big Data, 6(1), Article 1. https://doi.org/10.1186/s40537-019-0197-0

Tharwat, A. (2021). Classification assessment methods. Applied Computing and Informatics, 17(1), Article 1. https://doi.org/10.1016/j.aci.2018.08.003

Wilson, A. C., Roelofs, R., Stern, M., Srebro, N., & Recht, B. (2017). The Marginal Value of Adaptive Grad*ient Methods in Machine Learning*.

Yuni K, K. C., Hidayat, N., & Musfiroh, A. (2025). Closed-Loop Sytem In Sarangan Magetan Dairy Farm: Designing A Business Model Canvas For Resource Optimization. *Eqien - Jurnal Ekonomi Dan Bisnis*, *14*(2), 468–481. Https://Doi.Org/10.34308/Eqien.V14i2.1996