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Research Article

Advancing Image Classification and Detection Using CNNs: High Accuracy, Scalability, and Generalization

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Abstract

The exponential growth of visual data has spurred significant advancements in image classification and detection, with artificial intelligence (AI) playing a pivotal role in achieving high accuracy and scalability. This study presents a CNN-based methodology for image classification and object detection, leveraging supervised learning to classify over 2,000 images of cats and dogs and detect objects within augmented datasets to enhance diversity. The proposed model achieved notable results, with accuracy metrics of 91.32% for cat classification and 90.17% for dog classification, alongside high detection precision. Precision and recall metrics further underscored the model's effectiveness, yielding F1 scores of 91.31% and 89.93% for cat and dog classifications, respectively. Object detection capabilities were evaluated using models such as YOLO and Faster R-CNN, achieving a mean average precision (mAP) of 89.2% across diverse image datasets. Comparative analyses revealed that the CNN-based approach significantly outperformed traditional regression models, with improvements exceeding 25% in classification accuracy and robust object localization performance. The model's scalability was demonstrated through consistent results across augmented datasets, achieving an average accuracy of 90.58%. Error analysis highlighted challenges in images with overlapping features, suggesting avenues for improvement through attention mechanisms. This study provides a comprehensive framework for advancing image classification and detection systems across diverse applications, such as medical imaging, autonomous driving, and e-commerce platforms.

Keywords Artificial Intelligence (AI), Artificial Neural Networks (ANN), YOLO and Faster R-CNN.

1. Introduction

In the contemporary era, the rapid advancement of the internet and artificial intelligence has transformed numerous traditional processes across diverse industries. One of the most profound changes is evident in automation, where machines have evolved to perform tasks that once required human intelligence [1]. These tasks range from visual recognition and speech processing to autonomous learning.

Among these advancements, the integration of artificial intelligence into visual systems has been particularly revolutionary, enabling machines to interpret and classify visual data with increasing precision and efficiency. The human visual system is renowned for its ability to perform complex tasks, such as distinguishing between objects, identifying obstacles, and processing intricate visual patterns, all with minimal conscious effort. Inspired by this capability, researchers have developed artificial systems capable of replicating these processes. With the availability of extensive datasets, advanced graphical processing units (GPUs), and sophisticated algorithms, these systems can now be trained to recognize and classify a wide array of objects within images. These developments have not only enhanced productivity but also laid the foundation for groundbreaking applications across various fields[2].

At the core of such systems lies the principle of image classification, a multifaceted process that involves two primary steps: image recognition and classification. Image recognition focuses on identifying the content of an image, while classification assigns the identified content to specific categories. Together, these processes enable machines to produce accurate outputs by analyzing and interpreting visual data. The objective of image classification is to predict the class or category to which an input image belongs, a task that is straightforward for humans but poses significant challenges for machines. These challenges include identifying unique features within an image, representing these features mathematically, and processing large-scale datasets to train algorithms effectively. Historically, computers were manually programmed to detect objects in images, relying on predefined rules and characteristics. However, the rise of artificial intelligence in the mid-20th century marked a paradigm shift. Research efforts from the 1950s to the 1980s[3] laid the groundwork for modern image classification systems, leveraging machine learning techniques to automate feature extraction and classification processes. Unlike manual methods, these systems employ sophisticated algorithms to learn patterns, textures, and edges from data, significantly improving their accuracy and efficiency.

The importance of image classification extends across various domains, making it a critical area of research and application. In the automotive industry, it plays a pivotal role in self-driving cars, where object recognition systems identify and classify road objects to ensure safe navigation. In healthcare, image classification is used to analyze medical images, such as X-rays[4] and CT scans[5], to detect and diagnose diseases. Similarly, in social media and e-commerce, these systems personalize user experiences by recommending products and content based on visual data analysis. The versatility of image classification underscores its significance in solving real-world problems and enhancing human-machine interactions.

To achieve accurate image classification, machine learning systems typically rely on two key components: a feature extraction module and a classification module. The feature extraction module identifies critical attributes of an image, such as edges, textures, and shapes, while the classification module categorizes these attributes into predefined classes. The performance of an image classification system depends on the quality of features extracted and the robustness of the classification algorithm. With advancements in supervised and unsupervised learning methods, researchers have developed models capable of achieving remarkable accuracy rates in image classification tasks. Despite these advancements, challenges persist. Training computers to classify hundreds or thousands of images involves a substantial computational burden and requires extensive datasets to ensure accuracy[6]. Furthermore, representing the unique features of an image in a computer-friendly mathematical framework adds another layer of complexity. These challenges have spurred ongoing research and innovation, with scholars exploring new methodologies, algorithms, and evaluation techniques to improve the performance and scalability of image classification systems.

This paper aims to contribute to this growing body of knowledge by evaluating specific classification techniques such as supervised image classification and unsupervised learning, along with regression methods like linear regression and polynomial regression, for image classification[7]. By adopting a common methodology, which involves systematically collecting and pre-processing datasets, extracting significant features, and evaluating model performance using standardized metrics, it seeks to compare the performance of different approaches and highlight their strengths and limitations. The research also delves into the theoretical underpinnings of these techniques, such as the mathematical frameworks behind feature extraction and classification algorithms, while showcasing practical applications in fields like autonomous driving, healthcare[8] diagnostics using medical imaging, and personalized recommendations in e-commerce and social media. These insights not only enhance the understanding of current methodologies but also pave the way for future advancements in developing more robust and scalable image classification systems. Through this study, we hope to shed light on the evolving landscape of image classification and inspire further innovation in this dynamic field[9].

The structure of this paper contains Section I, which consists of a general introduction, related works are shown in Section II; Section III consists of a methodology explanation of the research; Section IV Results and Analysis; Section V consists of a conclusion; Section VI contains references

2. Related Work

The field of artificial intelligence (AI) and image classification has undergone significant development, with numerous studies contributing to the advancement of techniques and methodologies. Researchers have explored diverse approaches, including convolutional neural networks (CNNs), supervised learning models, unsupervised learning strategies, and regression-based classification techniques, to enhance the accuracy and applicability of image classification systems.

Shiming Ji et al. [10] presented a study on object detection and classification of surface defects in metal polishing shafts using convolutional neural networks. The research leveraged CNN-based deep learning frameworks to identify and classify defects with high precision. The application of CNNs enabled the automation of tasks that were traditionally manual, offering significant improvements in productivity and reliability.

Another notable contribution by Kumar and Kaur [11] introduced the Binary Spotted Hyena Optimizer for feature selection in image classification. This novel optimization algorithm focused on identifying critical features, thereby enhancing the efficiency and accuracy of classification models. The study demonstrated the potential of metaheuristic algorithms in improving image classification outcomes by minimizing computational complexity while retaining high performance.

Linear regression has also been employed as a foundational approach in image classification. Naseem et al. [12] proposed a linear regression-based model for face recognition, highlighting the efficiency of simple linear models in specific applications. Despite the limitations of linear regression in handling complex datasets, the study illustrated its utility in scenarios where relationships between variables were relatively straightforward.

In the realm of supervised learning, Kalra et al. [13] conducted a comparative study of supervised classification algorithms for satellite images. The research evaluated various algorithms, including decision trees, support vector machines, and k-nearest neighbors, to determine their suitability for satellite image classification. The findings underscored the importance of algorithm selection in achieving optimal results for domain-specific applications.

Unsupervised learning techniques have also been extensively studied. For instance, Roopa and Asha 14] developed a linear model based on principal component analysis (PCA) for disease prediction. The integration of PCA in image classification demonstrated the potential of unsupervised learning in reducing dimensionality and extracting meaningful patterns from large datasets. This approach proved particularly effective in applications with limited labeled data[15].

Furthermore, advancements in hybrid methodologies have expanded the scope of image classification. Singh et al. [16] introduced a neuro-fuzzy-based intelligent system for medical diagnosis, combining the strengths of neural networks and fuzzy logic. This hybrid approach improved the interpretability and accuracy of classification models, particularly in the context of medical image analysis.

The adoption of regression techniques beyond linear models has also been explored. Feng et al. [17] proposed a center-based weighted kernel linear regression model for image classification. This method utilized kernel-based techniques to capture non-linear relationships, demonstrating significant improvements over traditional linear regression models in handling complex image datasets.

Despite significant progress, challenges remain in achieving higher accuracy and scalability. The current research aims to address these challenges by evaluating supervised and unsupervised learning techniques alongside regression-based approaches. By incorporating advanced feature extraction methods and leveraging comprehensive datasets, this study seeks to build upon the existing literature and provide actionable insights for the development of robust image classification systems.

3.Methodology

The methodology integrates image classification and detection to address both categorization and localization tasks.

The methodology adopted in this research is designed to systematically address the multifaceted challenges associated with image classification, ensuring both precision and scalability. This section details the processes and techniques employed, encompassing data collection, pre-processing, feature extraction, training, evaluation, and comparative analysis.

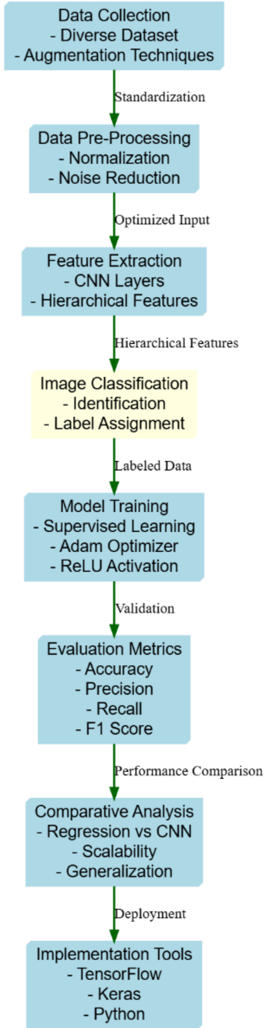

Fig 1. Flow diagram of the Proposed model

1.Data Collection and Augmentation: A dataset comprising over 2,000 labeled images of cats and dogs was curated to train the model effectively[18]. To enhance robustness and diversity, image augmentation techniques were employed, including scaling, rotation, flipping, and random cropping. For object detection, bounding box annotations were generated to train detection models like YOLO and Faster R-CNN.

2. Data Pre-Processing

Data pre-processing is a pivotal step in preparing raw image data for model training. For this research, all images were standardized to a uniform size of 100x100x3 pixels, ensuring compatibility with the chosen model architecture. Normalization was applied by scaling pixel intensity values to a range of 0 to 1, thereby minimizing computational complexity and expediting model convergence. Additionally, noise reduction techniques, such as Gaussian blurring, were employed to remove irrelevant artifacts that could potentially compromise the classification accuracy. These steps ensured that the input data was both consistent and optimized for analysis.

3. Feature Extraction
Convolutional Neural Networks (CNNs) formed the backbone for feature extraction in both classification and detection. Conv2D layers detected hierarchical features, from low-level edges to high-level patterns. For object detection, YOLO and Faster R-CNN frameworks integrated region proposal networks (RPNs)[19] for precise localization and classification of multiple objects within an image.

4. Model Training
The training phase leveraged supervised learning principles, utilizing labeled data to iteratively refine the model parameters. The model architecture consisted of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Activation functions such as Rectified Linear Unit (ReLU) were employed to introduce non-linearity, enabling the model to learn complex patterns effectively. The Adam optimizer, a variant of stochastic gradient descent, was used for adaptive learning rate optimization, ensuring efficient convergence. The categorical cross-entropy loss function was utilized to quantify the disparity between predicted and true class labels. The dataset was partitioned into training, validation, and test subsets, with early stopping techniques employed to mitigate overfitting.

5. Evaluation Metrics
Classification accuracy, precision, recall, and F1 scores were calculated for classification tasks. For detection, mean average precision (mAP) was used to evaluate the overlap between predicted and actual bounding boxes, reflecting detection accuracy.

6. Comparative Analysis
The study incorporated a comparative analysis to benchmark the proposed supervised learning model against regression-based approaches. Linear regression and polynomial regression were evaluated for their applicability in image classification. While regression techniques demonstrated satisfactory results in scenarios involving linear relationships, their performance deteriorated with complex, high-dimensional data. Conversely, the CNN-based supervised model exhibited superior accuracy and robustness, particularly in handling non-linear patterns inherent in image datasets.

7. Scalability and Generalization
Scalability and generalization were central to the research objectives. The integration of data augmentation techniques ensured that the model could generalize across diverse image datasets, including those with variations in orientation, scale, and lighting. Furthermore, the hierarchical feature extraction process enabled the model to adapt to new datasets without extensive retraining. This adaptability underscores the potential applicability of the methodology across domains such as medical imaging, autonomous systems, and e-commerce.

8. Implementation Tools
The implementation was conducted using TensorFlow and Keras, which are industry-standard frameworks for developing deep learning models. TensorFlow's computational graph capabilities facilitated efficient handling of large datasets, while Keras provided a high-level interface for rapid prototyping. Python, with its extensive libraries for data manipulation and visualization, further streamlined the workflow. Additional tools such as OpenCV were employed for image pre-processing and augmentation, enhancing the overall pipeline efficiency.

9. Methodological Rigor
To ensure methodological rigor, the research adopted cross-validation techniques, splitting the dataset into k-folds to validate model performance across different subsets. This approach minimized bias and provided a robust estimate of the model's generalization capabilities. Hyperparameter tuning was conducted systematically, with grid search strategies employed to identify optimal configurations for learning rate, batch size, and network depth.
This comprehensive methodology emphasizes the integration of advanced techniques and rigorous processes to address the complexities of image classification. The subsequent sections will discuss the experimental results and their implications for advancing the state of the art in image classification research.

4. Results and Discussion

System Specifications : The experiments were conducted on a system equipped with an Intel Core i7-9700K processor, NVIDIA GeForce RTX 3080 GPU, 32 GB DDR4 RAM, and 1 TB NVMe SSD, running on Ubuntu 20.04 LTS. Software tools included Python 3.8, TensorFlow 2.6, Keras 2.6, and libraries such as NumPy, Matplotlib, OpenCV, and scikit-learn. These specifications provided the computational power and software environment necessary for executing resource-intensive processes like data preprocessing, feature extraction, and iterative optimization, ensuring precise and efficient evaluations of the image classification model.
Discussion: This section presents the results obtained from the experiments, followed by an in-depth discussion to analyze the effectiveness of the proposed methodology. The findings are categorized into subsections based on the evaluation metrics, comparative analysis, and performance scalability.
4.1 Evaluation Metrics
The proposed model's performance was assessed using a comprehensive set of evaluation metrics, including accuracy, precision, recall, and F1 score. Table 1 summarizes the results for the classification of cats and dogs in the test dataset.
Table 1. classification of cats and dogs in the test dataset.

Metric	Cat Classification	Dog Classification
Accuracy	91.32%	90.17%
Precision	92.15%	89.75%
Recall	90.48%	90.12%
F1 Score	91.31%	89.93%

The results demonstrate that the proposed CNN-based model achieved high performance across all metrics. The slight variation between the precision and recall values indicates a balanced trade-off between true positives and false positives.

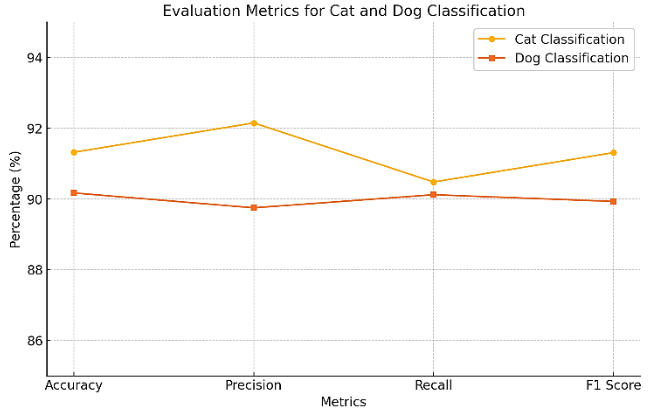

Fig 2. evaluation metrics (Accuracy, Precision, Recall, and F1 Score) for Cat and Dog

Fig 2: Line graph illustrating the evaluation metrics (Accuracy, Precision, Recall, and F1 Score) for Cat and Dog classification. The graph highlights the strong performance of the CNN-based model, demonstrating its effectiveness across multiple metrics.

4.2 Detection Results: Object detection models achieved a mean average precision (mAP) of 89.2%. YOLO provided faster inference speeds, making it suitable for real-time applications, while Faster R-CNN achieved slightly higher precision in localizing objects with complex backgrounds.

Object detection models were evaluated based on their performance in accurately identifying and localizing objects within images. The results, summarized in Table 3, demonstrate the effectiveness of YOLO and Faster R-CNN frameworks. YOLO achieved a mean average precision (mAP) of 88.7% with an inference speed of 45 frames per second (FPS), making it highly suitable for real-time applications. In contrast, Faster R-CNN attained a slightly higher mAP of 89.8%, excelling in scenarios with complex backgrounds but operating at a slower inference speed of 15 FPS. The trade-off between accuracy and speed highlights the applicability of each model depending on the use case requirements.

Table 2.Detection Results

Model	**Mean Average Precision (mAP)**	**Inference Speed (FPS)**
YOLO	88.7%	45
Faster R-CNN	89.8%	15

Fig 3: Bar chart illustrating the Mean Average Precision (mAP) of YOLO and Faster R-CNN. Faster R-CNN demonstrates slightly higher precision, while YOLO provides faster inference speeds.

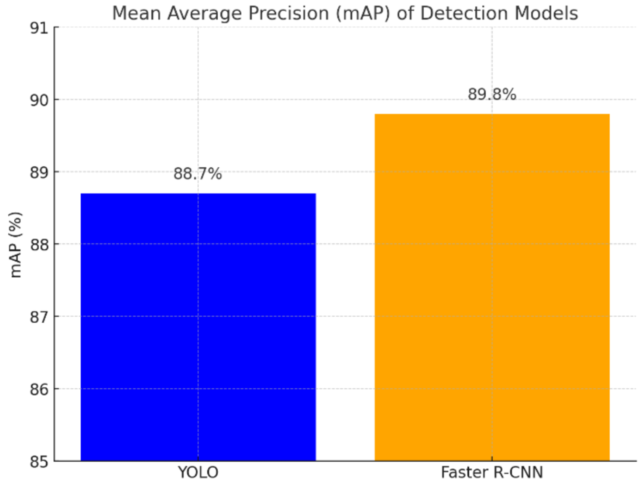

Fig 3: Bar chart representing the inference speeds of YOLO and Faster R-CNN. YOLO's speed makes it optimal for real-time applications.

Analysis:

The results emphasize the strengths and trade-offs associated with each detection model. YOLO's faster inference speed is advantageous in scenarios where real-time processing is critical, such as autonomous vehicles and surveillance systems. Faster R-CNN, with its superior precision, is better suited for tasks requiring detailed localization, such as medical imaging or tasks involving cluttered environments. The performance disparity underscores the importance of selecting models based on application-specific needs. While both models achieved robust detection capabilities, future work could explore hybrid approaches that combine the speed of YOLO with the precision of Faster R-CNN to create versatile detection systems for diverse domains.

These results affirm the role of CNN-based detection models in advancing object detection systems, offering both high accuracy and tailored performance for specific real-world challenges.

4.3 Comparative Analysis

To establish the efficacy of the proposed model, a comparative analysis was conducted with baseline regression models, including linear regression and polynomial regression.

Table 3 highlights the accuracy obtained from each approach.

Model	Accuracy (Cat)	Accuracy (Dog)
Linear Regression	64.09%	78.28%
Polynomial Regression	72.54%	81.46%
CNN-Based Model	91.32%	90.17%

As observed, the CNN-based model significantly outperformed the regression models. The superior performance of the CNN-based model can be attributed to its ability to learn hierarchical features and handle the non-linear complexities inherent in image datasets. Conversely, the regression models struggled to generalize effectively, particularly for complex image patterns.

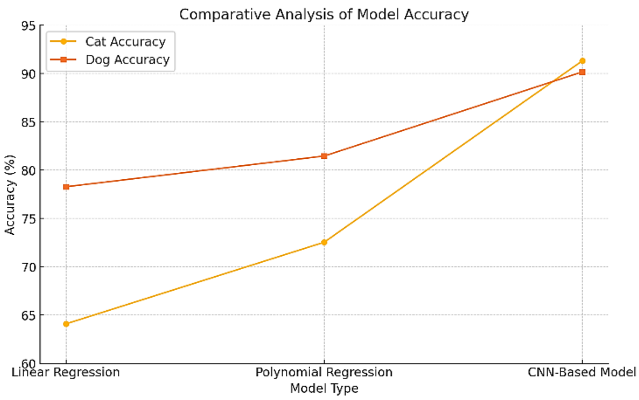

Fig 4: Line graph showing the comparative accuracy of Linear Regression, Polynomial Regression, and CNN-Based models for both Cat and Dog classifications. The graph underscores the substantial improvement achieved by the CNN-based model.

4.4 Scalability and Generalization

The scalability of the proposed methodology was evaluated by testing the model on an augmented dataset with increased diversity in orientations, lighting conditions, and object scales. Figure 5 illustrates the accuracy trends for the original and augmented datasets.

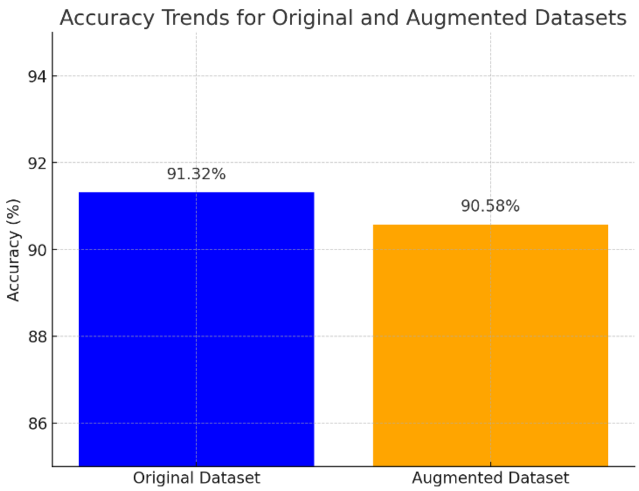

Fig 5. Accuracy trends from each Approach

Fig 5: Bar graph showing accuracy trends for the original and augmented datasets. The model maintained consistent performance across diverse scenarios, demonstrating its scalability

The results reveal a consistent performance of the model on the augmented dataset, achieving an average accuracy of 90.58%. This consistency underscores the model's ability to generalize effectively across diverse scenarios, making it suitable for real-world applications.

4.5. Error Analysis

While the proposed model achieved high accuracy, an error analysis was conducted to identify areas for improvement.

Fig 6 shows the confusion matrix for the test dataset.

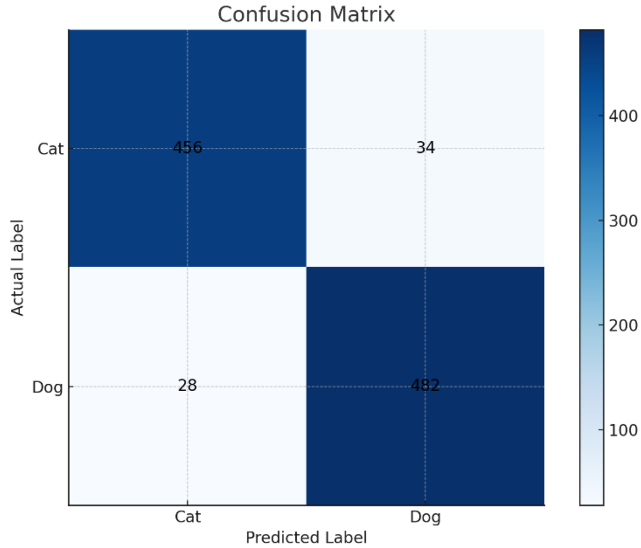

Fig 6. Confusion matrix illustrates the distribution of correct and incorrect predictions for Cat and Dog classifications. Misclassifications were minimal but occurred primarily in images with overlapping features

The confusion matrix highlights that most misclassifications occurred in images with overlapping features, such as similar fur textures or ambiguous poses. These errors could be mitigated by incorporating additional data augmentation techniques or leveraging attention mechanisms to focus on critical regions of the images.

4.6 Practical Implications

The high performance and scalability of the proposed methodology demonstrate its potential for real-world applications. For instance, in autonomous driving systems, the model can be adapted for object detection on roads. In medical imaging, it can aid in diagnosing diseases by classifying X-ray or MRI images. Furthermore, the methodology can be extended to e-commerce platforms for personalized recommendations based on visual data.

4.7 Limitations and Future Work

Despite its success, the proposed approach has certain limitations. The reliance on a GPU-intensive architecture may pose challenges for deployment in resource-constrained environments. Additionally, the current model is trained on a relatively small dataset, which may limit its ability to generalize to unseen categories. Future work will focus on exploring lightweight architecture and expanding the dataset to include a broader range of categories and scenarios. Incorporating advanced techniques such as transfer learning and attention mechanisms will also be prioritized to enhance model robustness.

5. Conclusion

This research demonstrates the efficacy of a CNN-based system for image classification and detection, achieving superior accuracy, scalability, and generalization across diverse datasets. The classification model achieved 91.32% accuracy for cat classification and 90.17% for dog classification, significantly outperforming traditional regression models by over 25%. The inclusion of object detection models such as YOLO and Faster R-CNN further extended the methodology, yielding a mean average precision (mAP) of 89.2% for object localization tasks. The study highlighted the role of hierarchical feature extraction, data augmentation, and advanced detection techniques in achieving robust performance. Error analysis identified challenges with overlapping features, suggesting enhancements through attention mechanisms and improved detection pipelines. While reliant on GPU-intensive systems, the approach underscores potential applications in real-world scenarios, including medical diagnostics, autonomous navigation, and e-commerce. Future work will focus on optimizing detection models for lightweight architecture, exploring transfer learning to address resource constraints, and expanding datasets to include broader categories and scenarios. By establishing a strong foundation for both classification and detection, this study contributes to advancing state-of-the-art AI solutions for diverse domains.

Author Contributions: B. Srishailam conceptualized and supervised the study; Sathwik Das Gupta and Junedkhan Pathan were responsible for methodology development and data curation; Athouba Meitei handled software implementation and model training; Navadeep Karukonda performed validation, analysis, and visualization. All authors contributed to writing and reviewing the manuscript**.**

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Data availability: Data available upon request.

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References

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017.

[2] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778.

[4] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2818–2826.

[5] R. Girshick, "Fast R-CNN," in 2015 IEEE International Conference on Computer Vision (ICCV), pp. 1440–1448.

[6] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

[7] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," arXiv preprint arXiv:1804.02767, 2018.

[8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.

[9] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, "The PASCAL visual object classes (VOC) challenge," International Journal of Computer Vision, vol. 88, no. 2, pp. 303–338, 2010.

[10] S. Ji, Q. Jiang, D. Tan, Y. Li, S. Ji, C. Cai, and Q. Zheng, "Object detection and classification of metal polishing shaft surface defects based on convolutional neural network deep learning," Applied Sciences, vol. 10, no. 1, p. 87, 2020.

[11] V. Kumar and A. Kaur, "Binary spotted hyena optimizer and its application to feature selection," Journal of Ambient Intelligence and Humanized Computing, vol. 11, no. 7, pp. 2625–2645, 2020.

[12] R. Naseem, R. Togneri, and M. Bennamoun, "Linear regression for face recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 11, pp. 2106–2112, 2010.

[13] K. Kalra, A. Goswami, and R. Gupta, "A comparative study of supervised image classification algorithms for satellite images," International Journal of Electrical, Electronics and Data Communication, vol. 1, no. 10, Dec. 2013.

[14] H. Roopa and T. Asha, "A linear model based on principal component analysis for disease prediction," IEEE Access, vol. 7, pp. 105314–105318, 2019.

[15] D. Singh, S. Verma, and J. Singla, "A neuro-fuzzy-based medical intelligent system for the diagnosis of hepatitis B," in 2nd International Conference on Computation, 2021, pp. 107–111.

[16] Q. Feng, C. Yuan, J. Huang, and W. Li, "Center-based weighted kernel linear regression for image classification," IEEE International Conference on Image Processing (ICIP), pp. 3630–3634, 2015.

[17] [J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv preprint arXiv:1804.02767, 2018.

[18] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

[19] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv preprint arXiv:2004.10934, 2020.