Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Messaging Application with Image Recognition and Classification Using Machine Learning

Dheeraj Seera[1, a),] Avinash Raj [2, b),] Nishant Gupta [3, c),] Himanshu[4, d),] Aman Deep[5, e)]
[1,2,3,4]*Department of Computer Science and Engineering,*
Lovely Professional University, Jalandhar, 140011, Punjab, India

Abstract- This study applies machine learning to messaging applications by using convolutional neural networks (CNNs) for image recognition and classification. With more and more photographs being exchanged in communications, efficient image processing has become crucial. To improve content management and user experience, also provides an automated technique for categorizing and evaluating photos that are received in messages. The study provides a detailed description of the architecture, implementation, and evaluation of the proposedsystem, highlighting its efficacious ability to detect photographs and enhance messaging applications in the era of visual communication.

Keywords: Image recognition, Image classification, Machine Learning, Convolutional Neural Network, Chat app, Dataset Collection, Data Pre-processing, Model Training and Evaluation.

I. Introduction

In this study, we leverage machine learning techniques, specifically convolutional neural networks (CNNs), to enhance messaging applications through automated image recognition and classification. The surge in photo exchanges within communications underscores the critical need for efficient image processing. Our approach aims to optimize content management and user experience by automating the categorization and assessment of received photos within messages. This paper provides a comprehensive overview of the system architecture, implementation details, and evaluation metrics, showcasing its effectiveness in photo detection and its role in advancing messaging applications in the era of visual communication. The application seeks to improve user experience and enable more effective content management by automating the analysis and classification ofshared photosthroughthe integration of CNN-based image recognition capabilities. For image feature extraction and classification, the approach makes use of pre- trained CNN models, with customization made to meet the needs of the messaging application. To streamline user interactions and content management, the Enhanced messaging applicationhad several key capabilities, such as automatic tagging and real-time image.

II. Literature review

Many research papers have investigated, via the use of natural language processing (NLP) tools, how messaging applications with machine learning (ML) capabilities impact user experiences. These studies analyze user interactions with such applications, focusing on areas like sentiment analysis, image recognition, and personalized recommendations. They explore the influence of ML algorithms on user engagement, response times, and overall satisfaction. The goal of this research is to enhance messaging app functionality through ML for improved user experiences across various domains.

Author Youhui Tian 2020 [1] proposed a method in which recurrent neural networks are introduced into the convolutional neural network to learn deep features of the image in parallel. The combination allows for capturing both spatial features through CNNs and sequential dependencies through RNNs. This hybrid approach can potentially improve the model's ability to recognize diverse features.

Authors Rahul Chauhan et al. 2018 [2] demonstrate the effectiveness of Convolutional Neural Networks (CNNs) for image and object recognition tasks, achieving high accuracy levels. Their study highlights CNNs' superiority over other algorithms, particularly in digit recognition, and explores various techniques to enhance CNN models' robustness, including ensemble classifiers and regularization methods.

Authors Muthukrishnan Ramprasath et al. 2022 [3] emphasizes the difficulty of automatic image classification in computer vision, citing past methods that achieved only basic classifications. The paper introduces a deep learning approach using Convolutional Neural Networks (CNNs) to classify grayscale images, achieving an impressive 98% accuracy on the MNIST dataset. This success showcases the effectiveness of CNNs for accurate automated image classification in computer vision tasks.

Author Hoo Wu et al. 2017 [4] proposed an optimized CNN- based image recognition model that addresses the issues of traditional image recognition methods often suffer from the use of unrelated regions in learning instances and a lack of consideration for instance weights in CNN models, leading to reduced accuracy. These issues were addressed by selecting regions using bottom-up region proposals and optimizing the model using an enhancement weight-based approach.

Authors Yanan sun et al. 2020 [5] introduced the Evolutionary paradigms that have been applied to neural network designs for two decades. Yet scaling to modern deep neural networks is hindered by complex architectures and numerous connection weights. CNNs have demonstrated superior performance in visual recognition tasks.

Authors Lan Wu et al. 2020 [6] an enhanced deep convolutional neural network model designed to address limitations of traditional CNNs, such as fewer convolutional layers and fixed kernel sizes. The proposed model dynamically assigns different convolutional kernels based on image complexity, resulting in improved information extraction and higher recognition rates in complex image recognition tasks.

Authors Enji Sun 2021 [7] discusses the development of image recognition technology driven by big data and enhanced computing capabilities. It introduces a convolutional neural. network designed for small-scale image recognition, optimizing model size and accuracy. RPCNet utilizes a parallel cascaded convolutional structure with jumper connections and different-scale convolution kernels to extract and fuse features, achieving significantly improved accuracy compared to AlexNet while maintaining a smaller network size.

Authors Sen Zhang et al. 2020 [8] introduced novel method that combines convolutional neural networks (CNNs) with autoencoders to overcome limited labeled data and fixed network structures. The approach uses a pre-trained CNN model with sparse autoencoder (SAE) to extract image features through multi-scale convolution and spectral analysis. By incorporating multiple channels with varied filters and sampling intervals, the method achieves enhanced recognition accuracy, with significant efficiency gains in pre-training time and a maximum recognition rate of 98.5%.

Authors Tianmei Guo et al. 2017 [9] analyzed the broad applications of deep learning, particularly convolutional neural networks (CNNs), in various image-related tasks. The paper focuses on a simple CNN model for image classification using benchmark datasets like MNIST and CIFAR-10. Additionally, it investigates the impact of learning rate settings and optimization algorithms on image classification performance within the CNN framework.

Authors Han Yaochang et al. 2019 [10] Aiming at the problem of remote sensing image classification, this paper designs an improved convolutional neural network structure. Combined with the transfer learning method, the classification experiments of different remote sensing image datasets are compared, and the effectiveness and versatility of the proposed method are verified.

Authors Keiron O'Shea et al. 2015 [11] provide an overview of Convolutional Neural Networks (CNNs) and their significance in image recognition tasks, highlighting their unique architecture that allows for efficient processing and analysis of image data. The review emphasizes the advantages of using CNNs for large-scale image datasets and discusses how CNN layers work together to transform input images into meaningful representations. Additionally, the paper outlines future directions for research in CNNs, including exploring new architectures, addressing interpretability challenges, and integrating CNNs with other machine learning technologies for improved performance.

Authors Matthew D. Zeiler at al. ECCV 2014 investigates the success of large Convolutional Network models on ImageNet and explores methods for improvement. It introduces a novel visualization technique to understand feature layers and classifier operations, leading to enhanced model architectures surpassing previous benchmarks. Additionally, an ablation study assesses the impact of different model layers, and the model's generalization is demonstrated by achieving state-of-the-art results on Caltech-101 and Caltech-256 after retraining the SoftMax classifier.

III. Objective of the paper

I. the objectives of the research paper regarding the influence messaging application to automate image recognition and classification encompass the following: - Develop a messaging application: Design and create a messaging platform that allows users to communicate through text and multimedia messages.

II. Integrate image recognition and classification using machine learning: Implement machine learning algorithms to recognize and categorize images uploaded or shared within the messaging app.

III. Enhance user experience through automatic identification and categorization of images: Automatically identify objects, scenes, or text in images to provide contextually relevant information and improve the user's messaging experience.

IV. Improve image search functionality within the app: Enable users to search for images based on their content, making it easier to find and share relevantimages in conversations.

V. Provide a more personalized messaging experience: Utilize image recognition to offer personalized suggestions or responses based on thecontent of the images shared in conversations.

VI. Detail the design, development, and evaluation of the application: Describe the process of designing and developing the messaging app, including the integration of machine learning for image recognition. Evaluate the app's performance in terms of user satisfaction and efficiency.

VII. Showcase the benefits of integrating machine learning for image recognition and classification: Highlight how the integration of machine learningenhances the functionality of the messaging app, providing users with a more intuitive and efficient way to communicate through image.

IV. Objective of this study

The primary objective of this research is to developa messaging application that utilizes machine learning for image recognition and classification. This application aims to enhance user experience by automatically analyzing and categorizing images shared within messages. The main points ofthis exploration are as follows:

• Develop a machine learning model for image recognition and classification tailored to the context of messaging applications.

• To integrate the chatbot into the e-commerce website's interface, enabling seamless interaction with users and providing real-time assistance during the shopping process.

• Evaluate the accuracy and efficiency of the image recognition and classification system within the messaging application.

• Hesitate user satisfaction and engagement with the messaging application enhanced by image recognition and classification features.

Explore opportunities for further improvement and optimization of the image recognition and classification system to enhance its performance in messaging applications.

V. Methodology

Data set collection to collect a dataset for the "Messaging Application with Image Recognition and Classification using Machine Learning project, define the scope to include models, cars, humans, and flowers. Select sources like online databases or image-sharing websites, ensuring permission to use the images. Organize the dataset into categories based on these labels. Preprocess the images by resizing, normalizing, and augmenting data as necessary for the machine learning model. Ensure the dataset is diverse and of high quality to train a robust model for image classification.

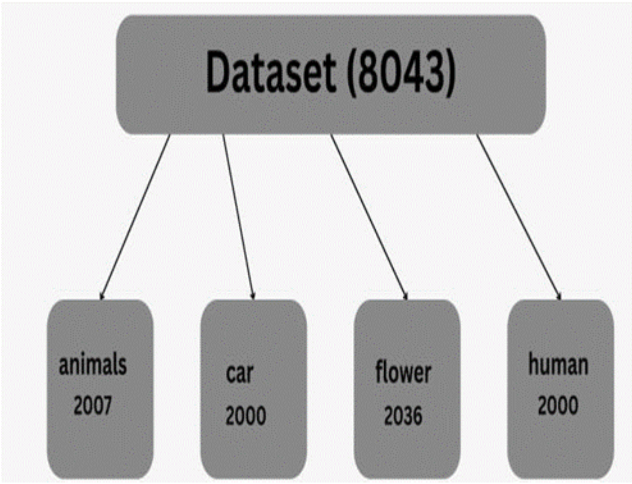
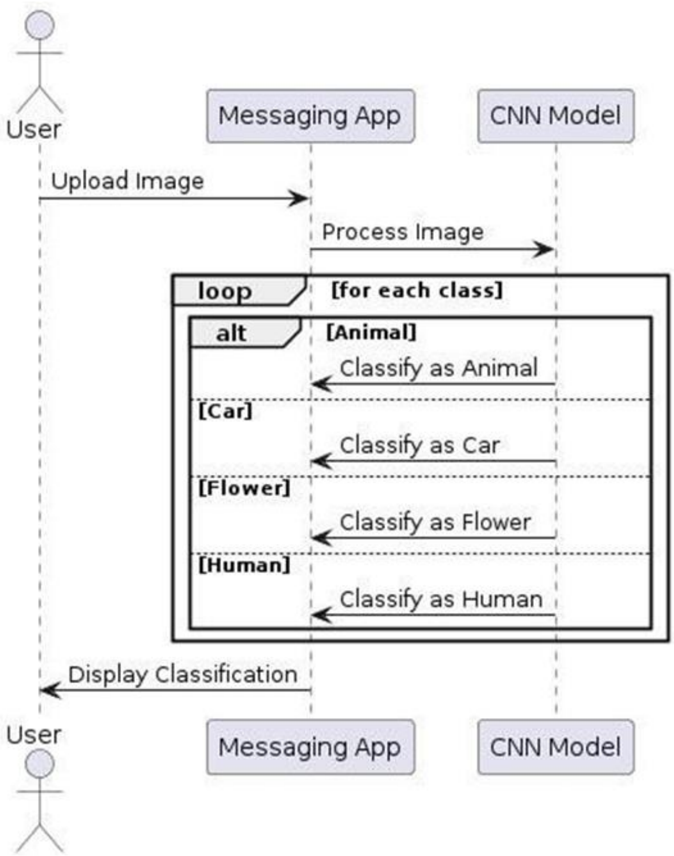


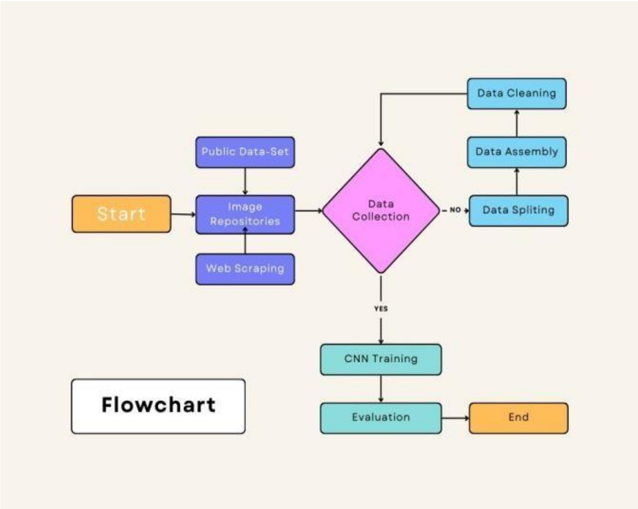
Figure 1

Data Set preprocessing - The dataset for the "Messaging Application with Image Recognition and Classification using Machine Learning" project consists of images of cars, flowers, and humans. Each category representsa distinct class that the machine learning modelwill be trained to recognize. The dataset may include various types of cars (e.g., sedans, SUVs), flowers (e.g., roses, sunflowers), and human poses or expressions. Each image in the dataset is labeled with its corresponding class (car, flower, or human) to facilitate supervised learning. The dataset'diversity and quality arecrucial for training a robust model capable of accurately classifying images in the messaging application.

Figure 2



Data Set information: - The dataset for the "Messaging Application with Image Recognition and Classification using Machine Learning" project consists of images representing four categories: models, cars, humans, and flowers. Thedataset is sourced from various online databases, social media platforms, and image-sharing websites, ensuring a diverse range of images for training and testing the model. Each image is labeled with its corresponding category to facilitatesupervised learning. The dataset is organized into training, validation, and testing sets, with the training set used to train the model, the validation set used to tune hyperparameters and prevent overfitting, and the testing set used to evaluate the model's performance. The images are preprocessedby resizing, normalizing, and augmenting the data to improve the model's ability to classify images accurately.



. Figure 3

VI. Preparing the model

The Proposed study used the CNN Image classification and recognition algorithm. To prepare the model for the "Messaging Application with Image Recognition and Classification using Machine Learning" project, begin by splitting the dataset into training, validation, and testing sets to evaluate the model's performance. Then, choose a suitable deep learning architecture, such as Convolutional Neural Networks (CNNs), that we have chosen for image classification tasks. Fine- tune the chosen model or use transfer learning to leverage pre- trained models like VGG, ResNet, or Mobile Net. Adjust hyperparameters, such as learning rate and batch size, through experimentation to optimize the model's performance. Finally, train the model on the training overfitting audit on the validation set to avoid overfitting, and evaluate its performance. The testing set to assess its accuracy in classifying images of models, cars, humans, and flowers.

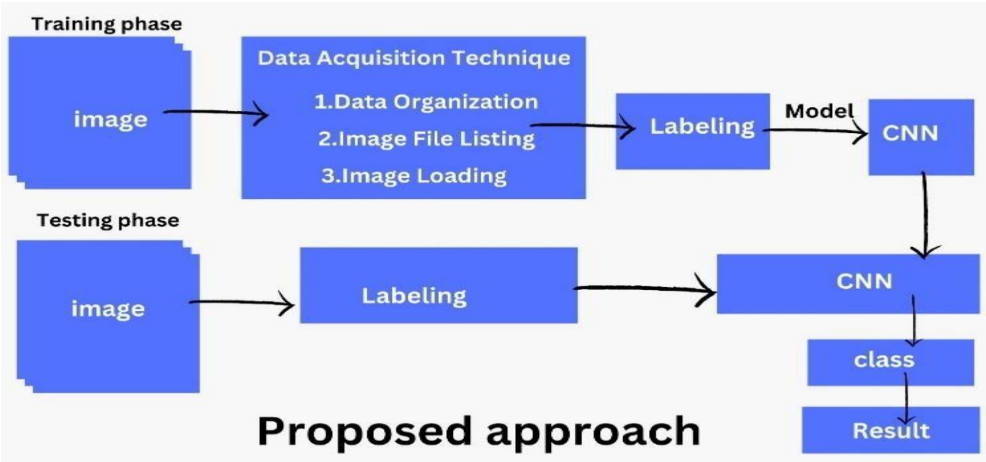


Figure 4

The CNN Architecture consists of multiple layers ofdata processing that is used in the proposed model.These layers consist of Conv2D layer, Dense layer,Dropout layer and Maxpolling layer. The conv2D layer extracts features from the input then the Denselayer performs at a higher level based on the features. The dropout layer prevents the system from overlifting to the training data.

And the Maxpolling layer reduces thedimensionality of the data and helps capture spatialfeatures while reducing the computational cost.

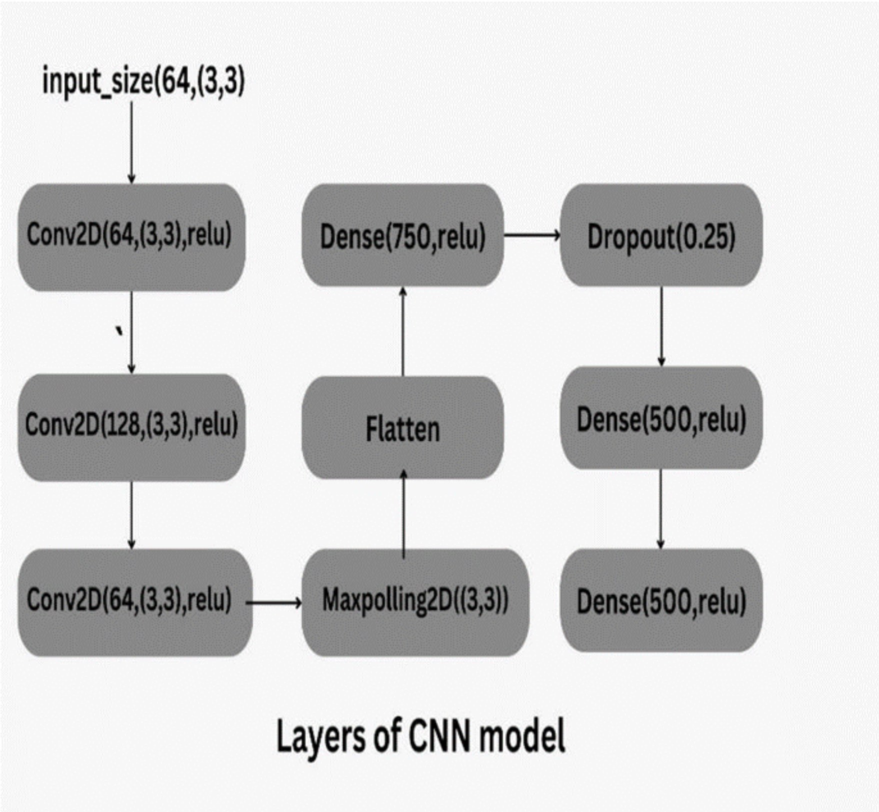


Figure 5

VII.Results and Model Evaluation

The trained model provides the accuracy of 98%.The below figure 6 represents the accuracy vsvalidation accuracy graph whereas figure 7represents the loss vs validation loss graph of thetrained model. When training machine learningmodels, the term “accuracy” is used to refer the model’s ability to correctly classify examples in thetraining dataset. On the other hand, validation accuracy or “val_accuracy” refer to the model’s ability to generalize and make accurate predictionson examples it has not seen before in the validationdataset. Similarly, “loss” indicates the error rate of the model during the training on the training dataset, while “validation loss” indicates the error rate of the model on examples in the validation dataset.

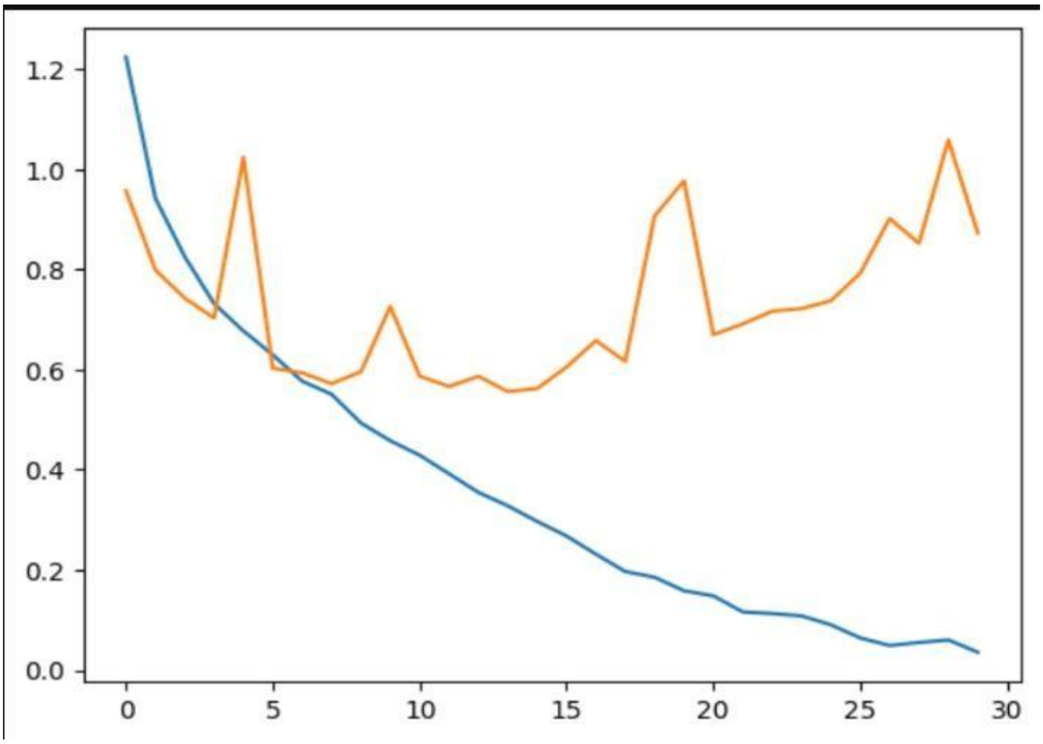


Figure 6. Accuracy vs validation Accuracy

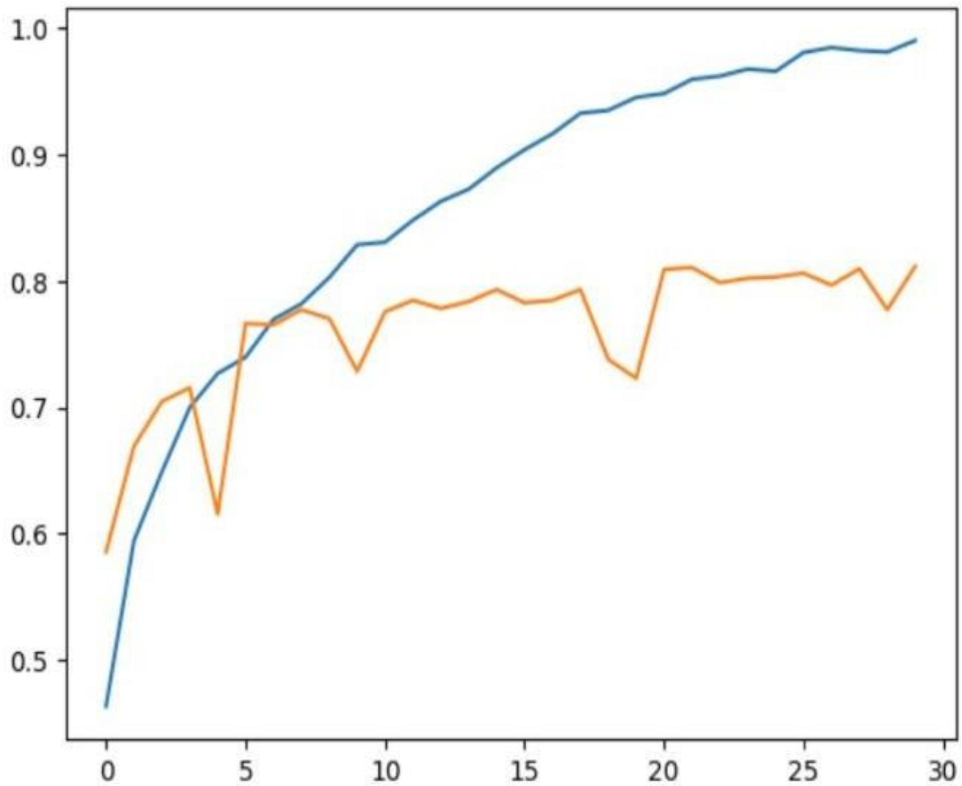


Figure 7. Loss vs Validation Loss

Epoch	Steps	Durationn/step	Accuracy	Loss	ValidationAccuracy	ValidationLoss
1.	189	210s	0.6928	0.7472	0.7156	0.7033
2.	189	210s	0.7251	0.6749	0.6156	1.0241
3.	189	214s	0.7365	0.6474	0.7663	0.6028
4.	189	222s	0.7678	0.5867	0.7653	0.5937
5.	189	220s	0.7885	0.5416	0.7772	0.5721
6.	189	217s	0.8054	0.4813	0.7703	0.5960
7.	189	225s	0.8330	0.4614	0.7285	0.7263
8.	189	222s	0.8293	0.4319	0.7757	0.5871
9.	189	1497s	0.8491	0.3964	0.7847	0.5665
10.	189	246s	0.9723	0.0820	0.7772	1.0590
11.	189	225s	0.9879	0.0416	0.8115	0.8735

In the table above, the accurate information of thevalidation accuracy, accuracy, validation loss andloss. The table presents a comprehensive overviewof a machine learning model's training progressover 30 epochs, with each epoch comprising of 189steps, it includes key performance metrics such astraining accuracy, training loss,validationaccuracy. And validation loss for each epoch,Notably, the training accuracy steadily improves from 0.6928 to 0.9879, indication the model'sincreasing proficiency in classifying data from thetraining set. Increasing proficiency in classifying data from the training set. Validation accuracyexhibits some fluctuations but generally rises overtime reaching its peak pf 0/8115 by the finalepochs, highlighting the model's ability to minimize errors and improve its performance.

VIII.Limitations

While incorporating CNNs for image recognition in a messaging app offers exciting features, it also introduces Challenges that are discussed as below:

:

Resource Limitations: Mobile devices might struggle to run CNNs efficiently, leading to batterydrain and potential slowdowns. Server-side processing also demands significant resources, especially during high user activity.

Data Challenges: Training a CNN effectively requires a vast amount of well-labelled data. In a messaging app setting, the variety and quality of user-uploaded images might be limited, impactingthe accuracy of image recognition.

Real-World Performance: Factors like poor lighting, blurry images, or cluttered backgrounds, which are common in user-uploaded photos, can lead to misclassifications by the CNN model.

Privacy Considerations: Uploading images to the messaging app raises privacy concerns. Robust security measures are crucial to prevent unauthorized access or misuse of image data used for training the CNN. Additionally, users should have clear control over whether their uploaded images are used for this purpose.

Accessibility and Connectivity: A stable internet connection is necessary for image recognition to function properly. Furthermore, it's important to consider accessibility for visually impaired users who might rely on more than just image recognition to understand message content.

IX. Conclusion

In conclusion, we have developed a Messaging applicationwith the Image detection and classification features using the Machine learning approaches. It has the potential to revolutionize the world. It presents intriguing possibilities, the benefits of image recognition while ensuring that a smooth, reliable and privacy. conscious environment for users. As the technology is getting to update by day passing. Thefeatures of image recognition and classification in chatting or messaging unlock a world of benefits.Sharing ideas becomes smoother with automatic captions and instant object identification. Chattinggets a boost of fun and engagement with playful filters and object recognition. Overall, this technology empowers a richer, more inclusive, andenjoyable chat experience.

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