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Classification & separation of WhatsApp images using machine learning

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ABSTRACT:

In this digital era, Internet has become an integral part of human lives. Internet and social networks have become very popular, allowing anyone to easily share pictures, text, audio and video files. Among all the applications, WhatsApp has become quite famous due to its ease of use and it has replaced almost all the other messaging apps. Apart from sending messages, images and videos over it, one more reason for the heavy usage of WhatsApp is the exchange of study notes and materials by the students during the time of the examination and end up with a lot of images to be deleted at the end of each semester. And also the notices and brochures in every semester gets mixed up with other images and these needs to be separated for easy reference. As the WhatsApp folder may have many other images, selecting the study material images, brochures, etc., one by one from the other images and then deleting them is a tedious process. Henceforth, this research work has utilized machine learning to build a model for detecting and extracting the images from the WhatsApp images folder. Further, the proposed model classifies the study notes images into printed and handwritten notes. Notices and brochures received on WhatsApp are separated into a new folder. And also, screenshots and photos are grouped into separate folders. The proposed model has been built by using a deep learning concept called the Convolutional Neural Network [CNN] and by using Python's Keras library. It takes an image and decides its category and then the action is taken accordingly.

INTRODUCTION :

Classifications are systematically divided into groups and categories based on their characteristics. Image classification has emerged to narrow the gap between computer vision and human vision by training computers with data. Image classification is achieved by classifying images into predetermined categories based on the content of the vision. Motivated by [1], this article describes the study of image classification using deep learning. Traditional image classification methods are part of the field of artificial intelligence (AI), formally known as machine learning. Machine learning consists of a feature extraction engine that extracts important features such as edges and textures, and a classification engine that classifies based on the extracted features. The main limitation of machine learning is that it can be separated, but it can only extract specific features on the image, not characteristic features from the training dataset. This shortcoming is eliminated by using deep learning [2]. Deep learning (DL) is a subfield of machine learning that can be learned by a unique calculation method. Deep learning models have been introduced to permanently decompose information in a homogeneous structure that humans encounter. To achieve this, deep learning uses a hierarchical structure of multiple algorithms, represented as an artificial neural system (ANN). ANN's architecture is simulated using the biological neural network of the human brain.

RELATED WORK :

The main aim of our work is to understand the performance of the networks for static as well as live video feeds. the primary step for the subsequent is to perform transfer learning on the networks with image datasets. this is often followed by checking the prediction rate of the identical object on static images and real-time video feeds. the various accuracy rates are observed and noted and presented within the tables given in further sections. The third essential criterion for assessing performance was to see if prediction accuracy differed among all CNNs used in the study. It must be noted that videos aren't used as a training dataset, they're used as testing datasets. Hence we are trying to find best image classifier where the object is the main attribute for classification of scene category. Different layers of the convolutional neural network used are: Input Layer: The primary layer of each CNN used is ‘input layer’ which takes images, resize them for passing onto further layers for feature extraction. Convolution Layer: The next few layers are 'Convolution layers,' which operate as image filters, allowing you to extract features from images and calculate match feature points during testing. Pooling Layer: The extracted feature sets are then passed to ‘pooling layer’. This layer takes large images and shrink them down while preserving the foremost important information in them. It keeps the utmost value from each window, it preserves the simplest fits of each feature within the window. Rectified Linear Measured Layer: The next ‘Rectified Linear Unit’ or ReLU layer swaps every negative number of the pooling layer with 0. This keeps learnt values from being stuck near 0 or berating toward infinity, allowing the CNN to remain mathematically stable. Fully Connected Layer.

EXISTING SYSTEM :

Our system will operate according to the system architecture depicted in the diagram below, capturing images either through a digital camera or through a database. For the next step, each image will be normalised to a predetermined size. We employ feature extraction approaches as M-BTC (Block Transition Coding), Histogram Equlization, and others to reduncate dimentianality.Feature vectors are formed by extracting features from a picture using various approaches such as MBTC (Block Transition Coding), Histogram Equlization, and so on.The NN will be given this processed image to use in the classification process.

PURPOSE :

Deep learning models include various image classification models used in real-world applications. Many methods have been

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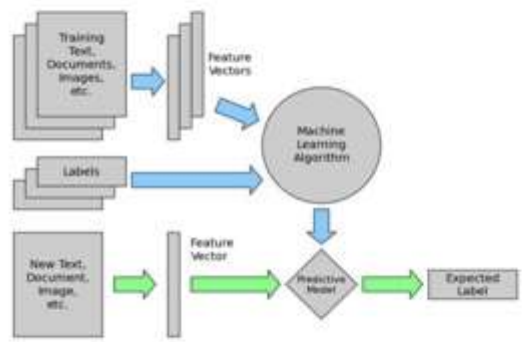
developed and are emerging. Therefore, here are some basics of other models compared to advanced CNNs. Deep Neural Networks (DNN) are used to train neural networks for regression and classification. DNN performance is not good for images due to its low accuracy. Convolutional Neural Networks (CNN) have proven to be very successful in image classification and objects. Identification, recognition, etc. Here, the results are highly optimized compared to DNN. However, with CNNs, the loss of verification is high, leading to overfitting. Transfer learning is another approach used to reuse acquired knowledge. This means that already trained models will be used in large datasets to get good results in the relevant work. However, the accuracy is high here and the time is shorter than other products

PROPOPSED SYSTEM :

In this project we are using CNN (convolution neural networks) algorithm to classify Whatsapp images to different categories such as Question Paper, Mark sheets, Printed papers, hand written papers and circular. CNN algorithm will get trained on above mention categories to build a classification model. This model can be applied on test images to predict image type.

To train CNN we have used same dataset given by and below showing that dataset images

SYSTEM ARCHITECTURE:



Methodology

The purpose of classification and separation of WhatsApp images using machine learning is to automate the process of organizing and categorizing images received through the WhatsApp messaging platform. This project aims to leverage machine learning techniques to analyze the content of WhatsApp images and classify them into specific categories or groups based on their visual features. The ultimate goal is to streamline the image management process and enable users to easily locate and access specific types of images within their WhatsApp media library.

By implementing image classification and separation using machine learning, the project aims to achieve the following objectives:

1. Efficient Organization: Manually sorting and organizing a large number of images received on WhatsApp can be time-consuming and tedious. The project seeks to automate this process, allowing users to quickly locate specific images by classifying them into predefined categories. This will

enhance efficiency and convenience in managing WhatsApp image collections.

2. Customizable Categories: The machine learning model will be trained to recognize and classify images into customizable categories based on user preferences. These categories can be defined according to specific themes, such as "family," "friends," "vacation," "work," or any other relevant criteria. By personalizing the categories, users can easily find and retrieve images that are meaningful to them.

3. Visual Feature Extraction: Machine learning algorithms will extract relevant visual features from WhatsApp images, such as color, texture, shape, or object recognition. These features will be used to train the model and enable it to accurately classify and separate images based on their visual characteristics. The aim is to develop a robust system that can handle various types of images and accurately categorize them.

4. Automation and Time-Saving: The project aims to eliminate the manual effort required for organizing WhatsApp images, reducing the time and energy spent on managing image collections. By automating the classification process, users can save valuable time and focus on other important tasks, thereby improving productivity and user experience.

5. Scalability and Adaptability: The proposed solution should be scalable to handle a large number of images and adaptable to different types of images commonly shared on WhatsApp. It should be capable of accurately classifying images despite variations in image quality, resolution, or format. The goal is to develop a versatile system that can handle a wide range of WhatsApp image scenarios.

The purpose of classification and separation of WhatsApp images using machine learning is to simplify and automate the organization and retrieval of images shared on the WhatsApp platform. By leveraging machine learning techniques and visual feature extraction, the project aims to create a user-friendly solution that can efficiently classify images into customizable categories, saving time and effort for users in managing their WhatsApp image collections.

Implementation

1. Image Classification Techniques:

Numerous studies have explored image classification techniques for organizing and categorizing images in various domains. Convolutional Neural Networks (CNNs) have been widely adopted for their ability to learn and extract meaningful features from images. Researchers have employed CNN architectures such as AlexNet, VGGNet, and ResNet to classify WhatsApp images into predefined categories or labels. Transfer learning, where pre-trained models are fine-tuned on WhatsApp image datasets, has also been explored to improve classification accuracy.

2. Feature Extraction and Representation:

Image feature extraction plays a vital role in image classification and separation tasks.

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Researchers have explored different feature extraction techniques, such as Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Speeded-Up Robust Features (SURF). These techniques extract salient visual features from WhatsApp images, enabling effective representation and subsequent classification.

3. Deep Learning Approaches:

Deep learning techniques have shown remarkable success in various computer vision tasks, including image classification. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been applied to capture temporal dependencies and context in WhatsApp image sequences. Additionally, Generative Adversarial Networks (GANs) have been used to generate new images and enhance image quality, contributing to better image separation and organization.

4. Semantic Segmentation:

Semantic segmentation involves assigning class labels to each pixel in an image, allowing for detailed separation and categorization. Fully Convolutional Networks (FCNs) and U-Net architectures have been employed for semantic segmentation tasks on WhatsApp images. This approach enables fine-grained separation of objects and backgrounds, facilitating more precise classification and organization.

5. Data Augmentation and Preprocessing:

Data augmentation techniques have been employed to address limited labeled data availability. Augmentation methods, such as rotation, flipping, and scaling, help generate additional training samples, reducing the risk of overfitting and improving classification performance. Preprocessing steps, including resizing, normalization, and denoising, have also been applied to enhance image quality and remove unwanted artifacts.

6. Evaluation Metrics:

To assess the performance of image classification and separation models, various evaluation metrics have been used. Common metrics include accuracy, precision, recall, and F1 score. Some studies have also employed Intersection over Union (IoU) or Dice coefficient to evaluate the quality of image segmentation results.

The classification and separation of WhatsApp images using machine learning techniques have witnessed substantial research and advancements in recent years. Researchers have explored image classification techniques, feature extraction and representation methods, deep learning approaches, semantic segmentation, data augmentation, preprocessing, and evaluation metrics. These efforts contribute to the development of effective models for automating the organization and categorization of WhatsApp images. By building upon the findings and methodologies from existing related work, researchers and practitioners can further enhance the accuracy and efficiency of image classification and separation algorithms in the context of WhatsApp.

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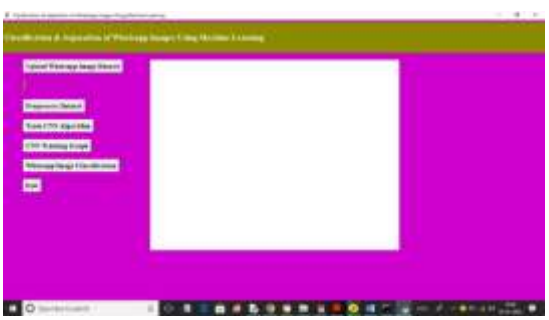
CNN Use:

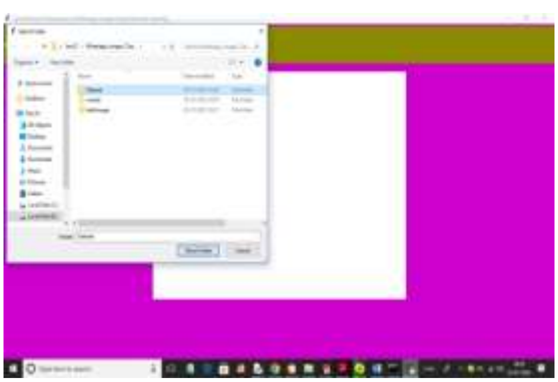
In this project we are using CNN (convolution neural networks) algorithm to classify Whatsapp images to different categories such as Question Paper, Mark sheets, Printed papers, hand written papers and circular. CNN algorithm will get trained on above mention categories to build a classification model. This model can be applied on test images to predict image type.

To train CNN we have used same dataset given by and below showing that dataset images

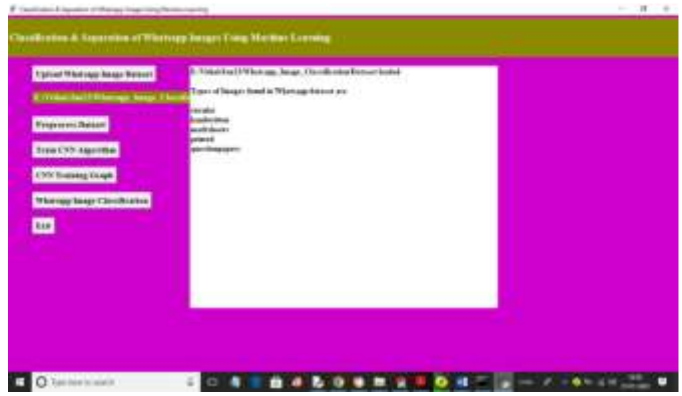
Results



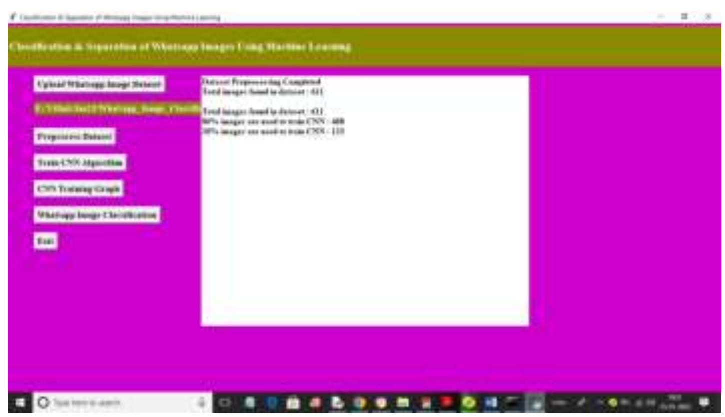
In above screen click on ‘Upload Whatsapp Image Dataset’ button to upload dataset and get below page



In above screen selecting and uploading ‘Dataset’ entire folder and then click on ‘Select Folder’ button to load dataset and get below page



In above screen we can see dataset loaded and then we can see types of categories loaded and now click on ‘Preprocess Dataset’ button to resize, normalize, shuffle and split dataset into train and test



In above screen we can see application found total 611 images in the dataset and then process and then took 488 images for training and 123 images for testing a 80 and 20%. Now click on ‘Train CNN Algorithm’ button to train CNN and get below output

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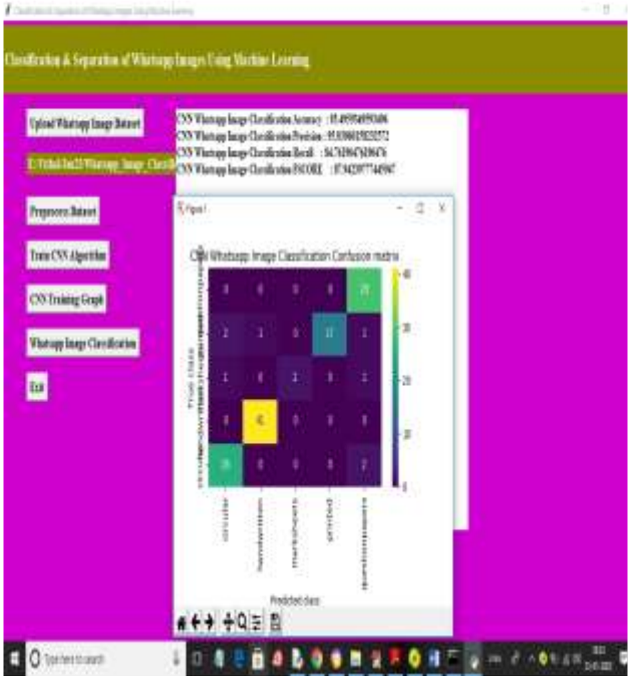
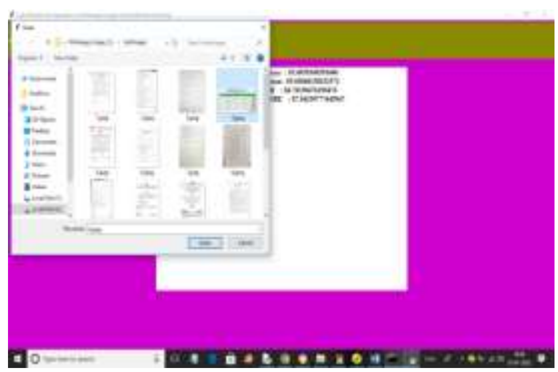
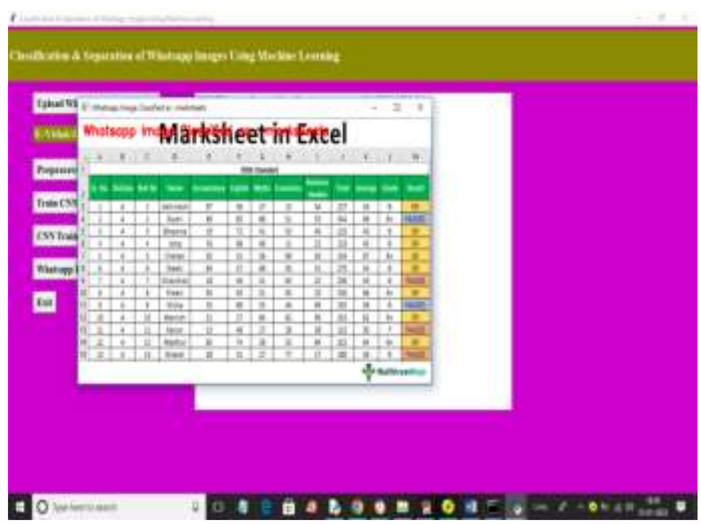


In above screen with CNN we got 93% accuracy and we can see precision, recall and FSCORE metric. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all blue colour boxes contains INCORRECT prediction count which are very few and different colour boxes contains CORRECT prediction count which are high in numbers so we got 93% accuracy. Now click on 'CNN Training Graph' button to get below page

In above CNN training graph x-axis represents training epoch and y-axis represents accuracy and loss values. Green colour line represents Training Accuracy and red colour line represents Training LOSS and in above graph we can see with each increasing epoch accuracy got increase and reached closer to 1 and loss got decreased and reached closer to 1. Now close above graph and then click on 'Whatsapp Image Classification' button to upload test image and get classification output



In above screen selecting and uploading 4.jpeg file and then click on 'Open' button to get below output



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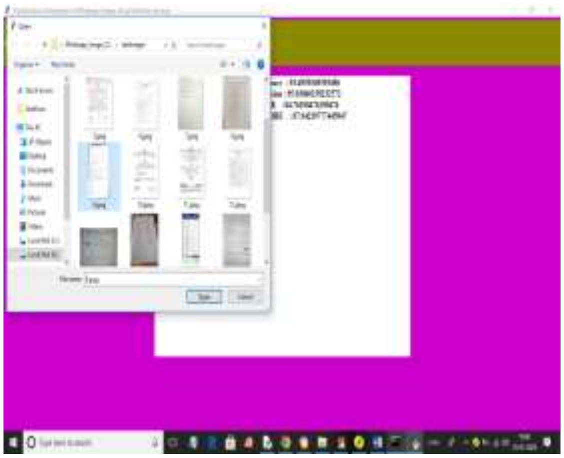
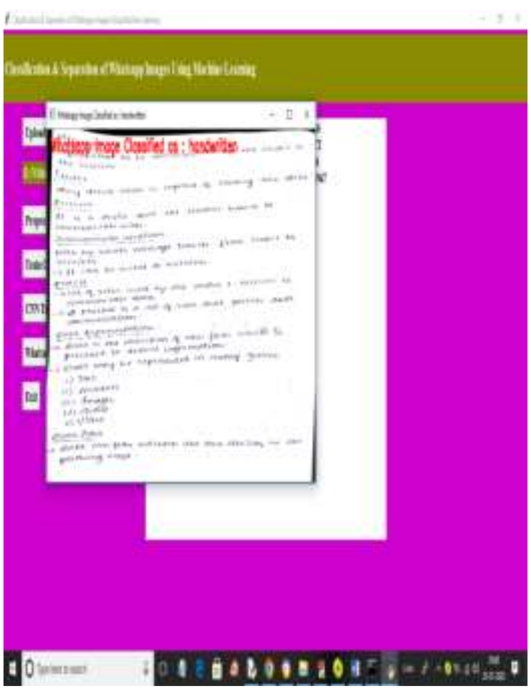
In above output image in red colour text or in image title you can see image classified as mark sheet. Similarly you can upload and test other images



In above screen uploading another image and below is the output



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