A Project Report

on

AN APPROACH FOR CYBERBULLYING DETECTION ON SOCIAL MEDIA

Submitted for partial fulfillment of the award of degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE ENGINEERING

by

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VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
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Accredited by NAAC with 'A' Grade - ISO 9001:2008 Certified
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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
B.Tech Programme Accredited by NBA

CERTIFICATE

This is to certify that this **Project Report** is the bonafide work of **Kurapati Jayasri, Kommineni Saran, Kathi Rakesh Adithya, Kotha Lakshmi Chandra Harsha,** bearing Reg. No. **20BQ1A05B6, 20BQ1A05A8, 20BQ1A0594, 20BQ1A05B2** respectively who had carried out the project entitled **"An Approach for Cyberbullying Detection on Social Media"** under our supervision.

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DECLARATION

I Kurapati Jayasri, Kommineni Saran, Kathi Rakesh Adithya, Kotha Lakshmi Chandra Harsha hereby declare that the Project Report entitled "AN APPROACH FOR CYBERBULLYING DETECTION ON SOCIAL MEDIA" done by me under the guidance of Mr. M. Kishore Babu at Vasireddy Venkatadri Institute of Technology is submitted in partial fulfillment of the requirements for the award of degree in Bachelor of Technology in Computer Science and Engineering. The results embodied in this report have not been submitted to any other University for the award of any degree.

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LIST OF ABBREVATIONS

CNN	Convolutional Neural Network
OCR	Optical Character Recognition
SVM	Support Vector Machine
RNN	Recursive Neural Network
IDE	Integrated Development Environment
ADAM	Adaptive Moment Estimation
UML	Unified Modelling Language
ER	Entity Relationship
REPL	Read-Eval-Print Loop
MVT	Model View Template
MVC	Model View Controller
PIL	Python Image Library
DFD	Data Flow Diagram
HDF	Hierarchical Data Format

ABSTRACT

In today's digital era, the proliferation of social media platforms has facilitated the rapid dissemination of harmful content, notably through images containing abusive language or offensive material. Recognizing the urgency of this issue, our project is dedicated to developing an intelligent system focused on detecting abusive content within images. Leveraging advanced machine learning techniques, particularly deep neural networks like CNNs, our aim is to construct a robust model capable of accurately identifying and categorizing such harmful imagery. Through extensive training on a diverse dataset, our objective is to equip the model with the capacity to recognize patterns indicative of abusive content.

Central to our project is the pressing concern of cyberbullying, which poses significant threats to individuals' well-being in online spaces. By addressing this issue head-on, we aim to develop an intelligent system tailored for detecting abusive posts across social media platforms. To ensure practicality and usability, we are crafting a user-friendly web application using the Python-based Django framework. Through this approach, we strive to empower users to navigate online environments more safely and contribute to the creation of a more secure online ecosystem.

Combining cutting-edge technology with a user-centric ethos, our project seeks to make meaningful contributions to fostering a safer online environment. By integrating advanced machine learning methodologies into a user-friendly web application, we aim to provide effective tools for detecting and mitigating abusive content on social media platforms. Through collaborative efforts, we aspire to create a more inclusive and respectful digital space for all user.

CHAPTER 1

1. INTRODUCTION

1.1 DESCRIPTION:

In today's digital landscape, social media platforms have transformed the way we communicate, offering unparalleled opportunities for interaction and engagement. However, this digital revolution also comes with a darker side: cyberbullying. Defined as the use of electronic communication to harass, intimidate, or humiliate individuals, cyberbullying poses a significant threat to the well-being and mental health of users worldwide. As social media usage continues to skyrocket, platforms like Facebook, Twitter, Instagram, and Snapchat have become breeding grounds for online harassment and abuse, with alarming percentages of adolescents and young adults reporting experiences of cyberbullying. Despite efforts to address this issue, cyberbullying persists as a pressing concern, necessitating innovative solutions to combat its escalation.

In response to this urgent need, our research endeavors to develop an intelligent system capable of detecting cyberbullying posts on social media platforms. By harnessing the power of machine learning techniques, particularly deep neural networks like CNNs, our objective is to construct a robust model capable of accurately identifying and categorizing abusive content, especially through images embedded with text. Through the integration of advanced technologies and user-friendly interfaces, our project seeks to empower social media platforms and users alike, facilitating prompt intervention and mitigation of cyberbullying incidents.

1.2 GOALS AND OBJECTIVES:

The research aims to develop an intelligent system to detect cyberbullying posts on social media platforms. By utilizing machine learning techniques, particularly CNNs, the objective is to construct a robust model capable of accurately identifying abusive content, especially in images with embedded text. Through advanced technology and user-friendly interfaces, the project seeks to empower platforms and users for prompt intervention.

CHAPTER 2

2.AIM AND SCOPE

AIM AND SCOPE OF THE PRESENT INVESTIGATION:

The primary aim of the present investigation is to develop an intelligent system dedicated to detecting abusive content within images, particularly memes circulated on social media platforms. By employing advanced machine learning techniques, including deep neural networks like CNNs, the objective is to construct a robust model capable of accurately identifying and categorizing abusive imagery. The investigation aims to address the concerning surge in harmful content dissemination online, particularly through images embedded with text featuring abusive language or offensive material.

The scope of the investigation encompasses the development of an intelligent system tailored for detecting abusive content within images, with a specific focus on memes shared across various social media platforms. Utilizing advanced machine learning methodologies, including deep neural networks, the investigation seeks to construct a model capable of accurately identifying and categorizing abusive imagery. Furthermore, the scope extends to the integration of user-friendly features into the system to ensure practicality and usability, facilitating seamless interaction between users and the application. Through exploration of diverse datasets and extensive training of the model, the investigation aims to contribute to the creation of a safer online environment by addressing the pressing issue of cyberbullying and harmful content dissemination on social media platforms.

Fig. 2.1. Abusive

Fig. 2.2. Non-Abusive

2.1 EXISTING SYSTEM:

The current landscape predominantly relies on text mining and natural language processing techniques to identify abusive content within textual posts on social media platforms. However, with the exponential growth of image-based communication, this approach may overlook abusive material embedded within images. The existing system faces limitations in effectively detecting abusive language present in image-text combinations, highlighting the need for a more comprehensive approach to content moderation. Thus, there is a clear gap in existing systems concerning the detection of abusive content within images, particularly memes shared on social media platforms.

2.2 PROPOSED SYSTEM:

The proposed system seeks to address the limitations of existing methods by adopting a multi-step approach to analyze images embedded with text for abusive content. Data collection involves sourcing images from various online platforms, including datasets like Memotion from Kaggle, comprising memes with textual content. Preprocessing steps ensure standardized and high-quality data input for model training, including image resizing and normalization. The system leverages pre-trained learning models like MobileNet for feature extraction and optical character recognition (OCR) to extract text from images. Incorporating dropout regularization during training, the model learns patterns and links between image attributes and abusive language presence, offering a more robust solution for detecting abusive content within images on social media platforms.

2.3 FEASIBLE STUDY:

2.3.1 ECONOMIC FEASIBILITY:

The project's economic feasibility lies in its potential to reduce the costs associated with cyberbullying incidents, such as healthcare expenses for mental health treatments and productivity losses due to psychological distress. Additionally, the implementation of the system may lead to cost savings for social media platforms by automating content moderation processes.

2.3.2 TECHNICAL FEASIBILITY:

The technical feasibility of the project is high, given the availability of machine learning frameworks and tools for image analysis. With advancements in deep learning algorithms and the widespread adoption of CNNs, building a robust model for cyberbullying detection is technically achievable. However, challenges may arise in data preprocessing and model optimization.

2.3.3 SOCIAL FEASIBILITY:

The project addresses a critical social issue by combating cyberbullying, which has far-reaching impacts on individuals, communities, and society as a whole. By empowering social media platforms and users with effective detection tools, the project aims to create a safer online environment conducive to positive interactions and well-being. Community support and collaboration will be essential for the successful implementation and adoption of the system.

2.4 LITERATURE REVIEW:

Waseem, Z., & Hovy, D. (2016). Hateful symbols or hateful people? Predictive features for hate speech detection on twitter. In Proceedings of the NAACL Student Research Workshop (pp. 88-93). The paper "Hateful symbols or hateful people? Predictive features for hate speech detection on Twitter" by Waseem and Hovy (2016) investigates the problem of hate speech detection on social media platform Twitter. The authors propose a machine learning approach to automatically detect tweets containing hate speech by analyzing a set of predictive features. The authors define hate speech as "speech that attacks a person or group on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender." They also note that hate speech can take many forms, including direct attacks, slurs, and coded language. To train their machine learning model, the authors collect a dataset of tweets labeled as containing hate speech or not containing hate speech.

Zhang, Y., & Wallace, B. (2016). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820.
The paper "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for

Sentence Classification" by Zhang and Wallace (2016) investigates the use of convolutional neural networks (CNNs) for sentence classification. The authors perform a sensitivity analysis to explore the effects of different hyperparameters on the performance of the CNN model, and provide a practical guide for practitioners on how to use CNNs effectively for sentence classification tasks. The authors use several benchmark datasets for sentence classification, including the Stanford Sentiment Treebank and the Movie Review dataset. They compare the performance of the CNN model to several other models, including support vector machines (SVMs) and recursive neural networks (RNNs). Through their sensitivity analysis, the authors identify several key hyperparameters that significantly affect the performance of the CNN model, including the number of filters, the filter size, and the dropout rate. They also provide recommendations for how to select appropriate hyperparameters based on the characteristics of the dataset and the specific task at hand.

Kumar, S., Aggarwal, A., & Singh, P. (2018). Offenseval: Identifying and categorizing offensive language in social media. arXiv preprint arXiv:1804.00058. The paper "OffensEval: Identifying and Categorizing Offensive Language in Social Media" by Kumar, Aggarwal, and Singh (2018) describes the Offensively shared task, which is a competition designed to encourage the development of machine learning models for identifying and categorizing offensive language in social media. The authors note that offensive language in social media can take many forms, including hate speech, cyberbullying, and harassment. They argue that automatic detection of such language is important for promoting a safe and respectful online environment. To create the Offense Eval dataset, the authors collect tweets labeled as offensive or non-offensive, as well as subtask-specific labels for different types of offensive language such as hate speech, abusive language, and targeted insult. They also provide guidelines for annotators to ensure consistency in labeling.

Kwok, I., & Wang, Y. (2013). Locate the hate: Detecting tweets against blacks. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing (pp. 1781-1791). The paper "Detecting tweets against blacks. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing" presents a study on automatically detecting tweets that contain negative sentiments towards African Americans. The authors use a dataset of tweets that were manually annotated for sentiment, and they experiment with various machine learning algorithms and feature sets to determine which ones perform best at identifying negative tweets. The study found that a combination of lexical, syntactic, and semantic features, along with a Support Vector Machine (SVM) classifier,

achieved the highest accuracy in detecting negative tweets. The authors also identified specific words and phrases that were strongly associated with negative sentiment towards African Americans, such as racial slurs and derogatory terms.

2.5 SYSTEM REQUIREMENTS:

System requirements refer to the hardware, software, and other configurations necessary for a computer system or software application to operate effectively. These requirements typically include specifications for hardware components such as processors, memory, storage, and peripherals, as well as software requirements like operating systems, programming languages, libraries, and frameworks.

2.5.1 HARDWARE REQUIREMENTS:

Hardware requirements specify the physical components necessary for a computer system or software application to function properly. This includes specifications for the processor, memory (RAM), storage (hard disk), input devices (keyboard, mouse), output devices (monitor), and any other peripherals required for operation.

- Processor: Intel Core i3 or equivalent
- Hard Disk: Minimum 160GB
- Keyboard: Standard Windows Keyboard
- RAM: Minimum 8GB
- Monitor: SVGA Monitor

2.5.2 SOFTWARE REQUIREMENTS:

Software requirements outline the necessary software components and configurations needed for a computer system or software application to run correctly. This includes the operating system, programming languages, libraries, frameworks, server-side scripts, integrated development environments (IDEs), and any other software dependencies required for development or execution.

- operating System: Windows 7/8/10
- Server-side Script: HTML, CSS, Bootstrap & JavaScript

- Programming Language: Python
- Libraries: Pandas, OS, NumPy
- IDE/Workbench: PyCharm
- Technology: Python 3.6+
- Database: Sqlite3

2.6 MODULES:

Project modules play a pivotal role in software development, serving as discrete units that encapsulate specific functionalities or features. These modules are designed to enhance organization and management within a project, breaking down complex tasks into manageable components. By promoting modularity and reusability, project modules facilitate easier maintenance and scalability throughout the project's lifecycle.

System:

Collect dataset: The system will collect the dataset from the user.
Preprocess: Then, the system will preprocess the collected data.
Training: The next step is to train the data which was collected from dataset.
View image: The system will view the image which was sent by the user.
Predict: Then the system will predict the results.
Logout: Finally, the system should logout.

User:

Register: User has to register with username, password, email and phone number.
About project: User need to know about the project before he collected dataset from the system.
Login: User must login with their valid credentials.
Upload image: User will upload the image for output.
View prediction: User can see the predicted value done by the system.
Logout: Then, user must logout.

CHAPTER 3

3.CONCEPTS AND METHODS

Abusive Content Detection:

The primary concept involves identifying and categorizing abusive content within images, particularly memes shared on social media platforms. Abusive content encompasses offensive language, derogatory remarks, hate speech, or harmful imagery aimed at disparaging individuals or groups.

Machine Learning:

Machine learning plays a crucial role in training models to recognize abusive content within images. Techniques such as deep learning, including convolutional neural networks (CNNs), are utilized to classify images based on their content and identify patterns indicative of abusive language or offensive material.

3.1 Concepts:

3.1.1 MOBILENET ARCHITECTURE:

MobileNet is a convolutional neural network (CNN) architecture specifically designed for mobile and embedded vision applications. It is characterized by its lightweight structure, making it suitable for deployment on resource-constrained devices such as smartphones and IoT devices. MobileNet employs depthwise separable convolutions, which significantly reduce the computational cost and model size compared to traditional convolutional layers.

In MobileNet, each convolutional layer is split into two separate layers: a depthwise convolutional layer and a pointwise convolutional layer. The depthwise convolutional layer applies a single filter to each input channel separately, followed by a pointwise convolutional layer that combines the outputs of the depthwise convolution across channels. This depthwise separable convolutional approach reduces the number of parameters and computational complexity while maintaining expressive power.

MobileNet architectures are characterized by their depth multiplier parameter, which controls the number of channels in each layer, allowing for trade-offs between model size and performance. By adjusting the depth multiplier, developers can tailor MobileNet models to suit the specific requirements of their applications, balancing computational efficiency with accuracy.

Additionally, MobileNet architectures often incorporate techniques such as batch normalization and ReLU activation functions to further enhance performance and training stability. Batch normalization helps in normalizing the inputs to each layer, reducing internal covariate shift.

3.1.2 CNN ARCHITECTURE:

Convolutional Neural Networks (CNNs) are a class of deep learning architectures designed for processing structured grid-like data, such as images. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers are stacked sequentially, with each layer extracting hierarchical features from the input data.

In CNN architectures, convolutional layers apply filters (kernels) to the input image, extracting local features through convolution operations. Pooling layers down sample the feature maps produced by the convolutional layers, reducing spatial dimensions and preserving important features. Fully connected layers combine the features extracted by convolutional and pooling layers to perform classification or regression tasks.

CNN architectures can vary in depth, width, and connectivity patterns, depending on the specific task and dataset. Deep CNN architectures, with multiple layers of convolution and pooling, have demonstrated remarkable success in tasks such as image classification, object detection, and semantic segmentation.

3.1.3 ADAM OPTIMIZER:

Adam (Adaptive Moment Estimation) is an optimization algorithm commonly used for training deep neural networks. It combines the advantages of two other popular optimization techniques: AdaGrad and RMSProp. Adam maintains two moving averages of gradients: the first moment (mean) and the second moment (uncentered variance). These moving averages are used to adaptively adjust the learning rates for each parameter during training.

The key features of the Adam optimizer include:

Adaptive Learning Rates:

Adam adapts the learning rates for each parameter individually based on their gradients' first and second moments. This adaptive learning rate scheme allows Adam to converge faster and more robustly than fixed learning rate methods.

Bias Correction:

Adam incorporates bias correction terms to compensate for the initialization bias of the moving average estimates. This helps to improve the convergence speed of the optimizer, especially during the early stages of training.

Regularization:

Adam includes L2 regularization by default, which penalizes large parameter values to prevent overfitting. This regularization term helps to generalize the model and improve its performance on unseen data. This implicit regularization not only helps prevent overfitting but also fosters the learning.

As a result, Adam-equipped models demonstrate improved performance on diverse datasets, exhibiting heightened resilience to noise and variability inherent in real-world data.

3.2 METHODS:

3.2.1. DATA COLLECTION:

The data collection process involves sourcing images from a variety of online platforms and social media channels, including datasets such as the Memotion Dataset available on Kaggle. The Memotion Dataset, comprises approximately 6,992 images, primarily consisting of memes. These images contain textual content, and annotations are provided to indicate the presence of abusive language. The dataset is meticulously curated to ensure a diverse representation of abusive language types and non-abusive text samples. This diversity enhances the model's ability to generalize and accurately detect abusive language within images.

	A	B	C	D	E	F	G	H	I
1		image_name	text_ocr	text_corrected	humour	sarcasm	offensive	motivational	overall_sentiment
2	0	image_1.jpg	LOOK THERE	LOOK THERE MY	hilarious	general	not_offen:	not_motivation:	very_positive
3	1	image_2.jpeg	The best of #	The best of #10 Y	not_funny	general	not_offen:	motivational	very_positive
4	2	image_3.JPG	Sam Thorne (	Sam Thorne @St	very_funny	not_sarcas	not_offen:	not_motivation:	positive
5	3	image_4.png	10 Year Chall	10 Year Challeng	very_funny	twisted_m	very_offer	motivational	positive
6	4	image_5.png	10 YEAR CHA	10 YEAR CHALLEI	hilarious	very_twist	very_offer	not_motivation:	neutral
7	5	image_6.jpg	1998: "Don't	1998: "Don't get	hilarious	general	slight	motivational	negative
8	6	image_7.png	10 years chal	10 years challeng	not_funny	not_sarcas	not_offen:	not_motivation:	negative
9	7	image_8.jpg	10 Year Chall	10 Year Challeng	very_funny	twisted_m	not_offen:	not_motivation:	neutral
10	8	image_9.jpg	Fornite died i	Fornite died in 1(	funny	not_sarcas	slight	motivational	positive
11	9	image_10.png	FACEBOOK '1	FACEBOOK '10 YE	funny	general	slight	motivational	positive
12	10	image_11.jpg	PROBABLY TI	PROBABLY THE F	funny	general	very_offer	motivational	negative
13	11	image_12.jpg	State Dining I	State Dining Roo	not_funny	very_twist	very_offer	not_motivation:	very_positive
14	12	image_13.png	I did the Face	I did the Faceboo	very_funny	general	not_offen:	not_motivation:	positive
15	13	image_14.png	IFIDOWNLO/	IFIDOWNLOADA	funny	general	not_offen:	not_motivation:	positive
16	14	image_15.jpg	Anti-vaxx kid	Anti-vaxx kids wh	not_funny	not_sarcas	not_offen:	not_motivation:	very_negative

Fig. 3.1 Labelled Data

3.2.2. DATA PREPROCESSING:

Before the collected data can be fed into the model for training, preprocessing steps are applied to ensure its suitability and quality. Image preprocessing includes resizing and normalization to standardize input dimensions, facilitating efficient model training special emphasis is placed on resizing and rescaling the images to ensure uniformity in input dimensions.

Resizing involves adjusting the dimensions of each image to a standardized size, typically required by the model architecture being used. This step is crucial for maintaining consistency in the input data and facilitating efficient model training. ImageDataGenerator and data augmentation is beneficial in machine learning, as it allows us to artificially increase the size and diversity of our dataset, improving the ability of models to generalize. Additionally, rescaling of images is performed to normalize pixel values and bring them within a specific range, typically between 0 and 1. Rescaling ensures that the

model receives input data with consistent intensity levels, which aids in improving the convergence speed and performance of the training process.

By rescaling the images, potential variations in brightness, contrast, and overall intensity are minimized, leading to more stable and reliable model predictions. They not only standardize the input dimensions but also enhances the model's ability to learn meaningful patterns and features from the images. Additionally, measures are taken to handle missing data and address any imbalances in the dataset to prevent biases during model training.

3.2.3. ALGORITHM AND MODEL:

The methodology begins by utilizing pre-trained learning models like MobileNet for feature extraction from images. Subsequently, optical character recognition (OCR) technology, such as Tesseract OCR, is employed to extract text from images.

MobileNet architectures often incorporate techniques such as batch normalization and ReLU activation functions to further enhance performance and training stability. Batch normalization helps in normalizing the inputs to each layer, reducing internal covariate shift.

This fusion of machine learning with OCR offers a practical approach to online safety and content regulation. The system further incorporates optimization techniques like the Adam optimizer and Convolutional Neural Network (CNN) models to effectively detect offensive content within images.

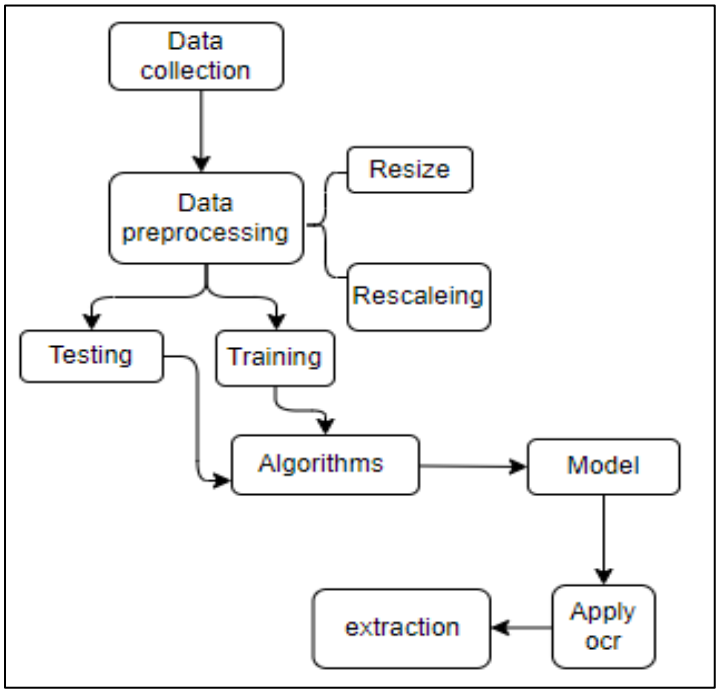


Fig. 3.2. Work-Flow Diagram

3.3 SYSTEM DESIGN:

Input Design:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc. Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties –

- It ensures proper completion with accuracy.
- It should be easy to fill and straightforward.
- It should focus on user's attention, consistency, and simplicity.
- All these objectives are obtained using the knowledge of basic design principles regarding

Objectives for Input Design:

The objectives of input design are:

- **Accuracy:** Input design should facilitate accurate data entry by providing appropriate validation checks, error handling mechanisms, and user feedback to prevent or correct input errors.
- **Completeness:** Input design should capture all necessary data required for the system to perform its functions effectively. It should prompt users to enter all relevant information and ensure that no essential data fields are left blank.
- **Ease of Use:** Input design should be user-friendly and intuitive, minimizing the cognitive load on users and streamlining the data entry process. It should use familiar input formats and provide clear instructions to guide users through the data entry process.

Output Design:

The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report.

Objectives of Output Design:

The objectives of output design are:

- **Clarity:** The output should be clear and easily understandable to the intended audience. This involves using language, formatting, and visuals that are appropriate for the users' knowledge.

- **Accuracy:** The information presented in the output should be accurate and reliable. Any calculations, data, or text should be free from errors or misleading information.
- **Relevance:** The output should provide relevant information that is useful to the users' needs and tasks. Unnecessary or extraneous information should be avoided.

3.4 UML DIAGRAMS:

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software system, as well as for business modelling and other non-software systems.

3.4.1 GOALS:

The Primary goals in the design of the UML are as follows:

- Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
- Provide extendibility and specialization mechanisms to extend the core concepts.
- Be independent of particular programming languages and development process.
- Provide a formal basis for understanding the modelling language.
- Encourage the growth of OO tools market.
- Support higher level development concepts such as collaborations, frameworks, patterns and components.
- Integrate best practices.
- Foster collaboration among stakeholders by providing a common language for communication and understanding throughout the software development lifecycle.
- Promote reusability and maintainability by facilitating the creation of modular and well-structured models.

3.4.2 USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. Use Case diagram is to show what system functions are performed.

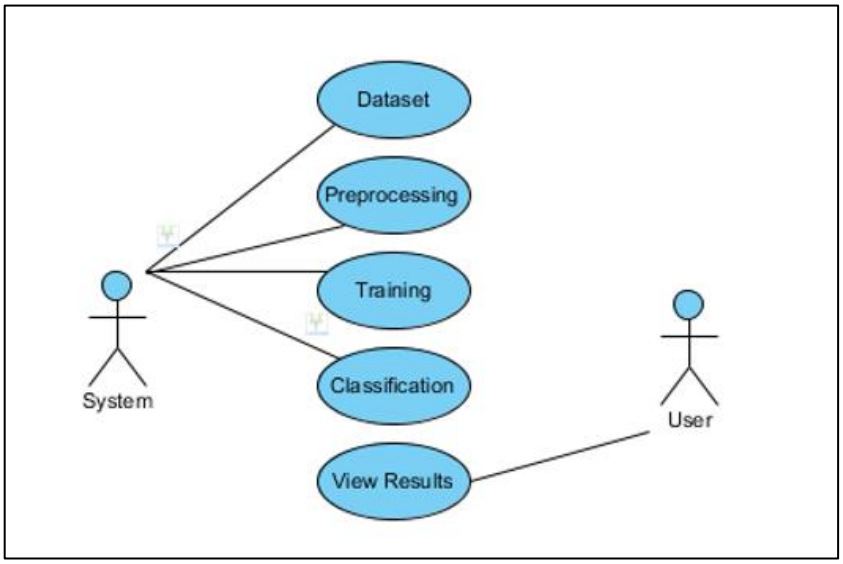


Fig. 3.3. Use Case Diagram

3.4.3 CLASS DIAGRAM:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes.

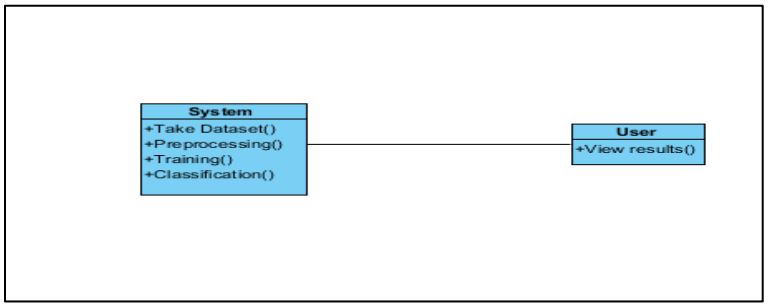


Fig. 3.4. Class Diagram

3.4.4 SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

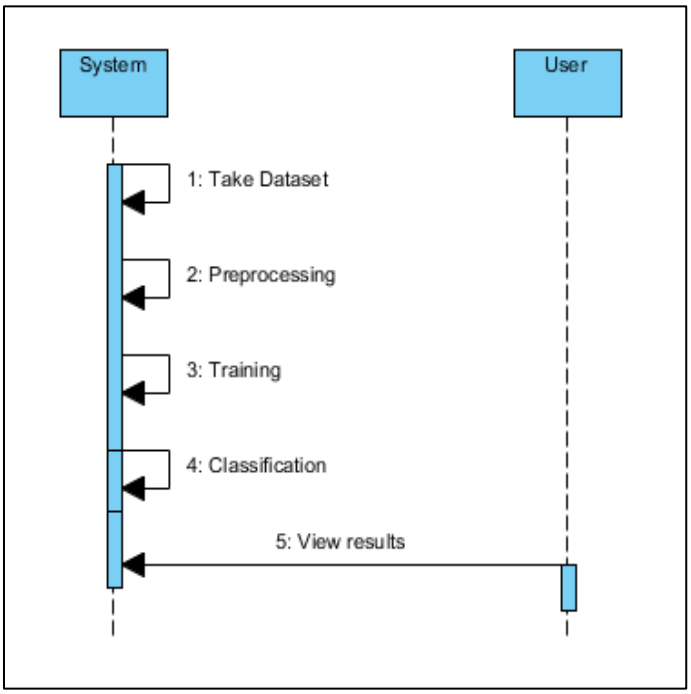


Fig. 3.5. Sequence Diagram

3.4.5 COLLABORATION DIAGRAM:

In collaboration diagram the method call sequence is indicated by some numbering technique as shown below. The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram. The method calls are similar to that of a sequence diagram. But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization. Collaboration diagrams can be particularly useful for understanding the structural organization of objects within a system and how they work together to accomplish a common goal. They can also aid in identifying potential bottlenecks or inefficiencies in the communication between objects, allowing for optimization and improvement of the system's design. They highlight the relationships and interactions between objects.

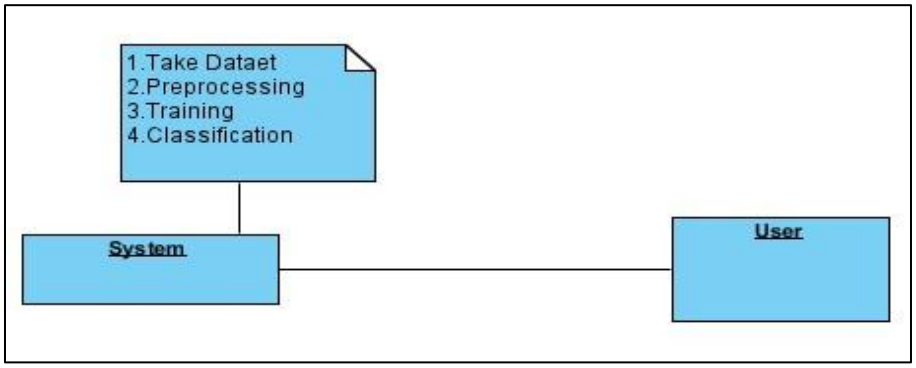


Fig. 3.6. Collaboration Diagram

3.4.6 DEPLOYMENT DIAGRAM:

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical hardware's used to deploy the application.

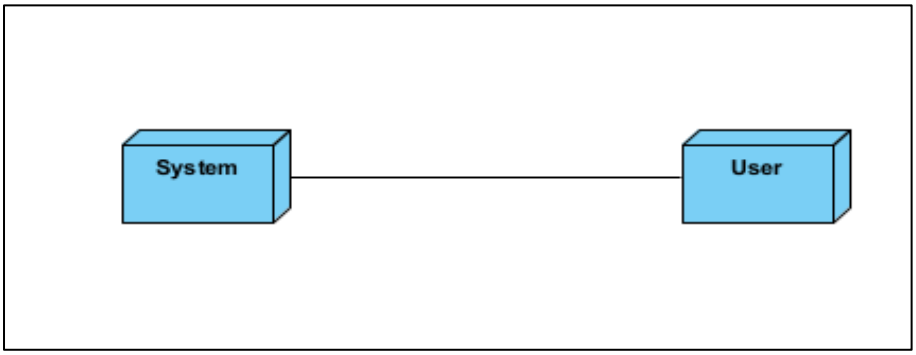


Fig. 3.7. Deployment Diagram

3.4.7 ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modelling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control. They provide a visual means to illustrate various paths through a process, including alternative scenarios and exception handling. This versatility makes activity diagrams a valuable tool for analyzing, communicating, and refining the design of both business processes and software systems, aiding in requirements elicitation, system design, and validation.

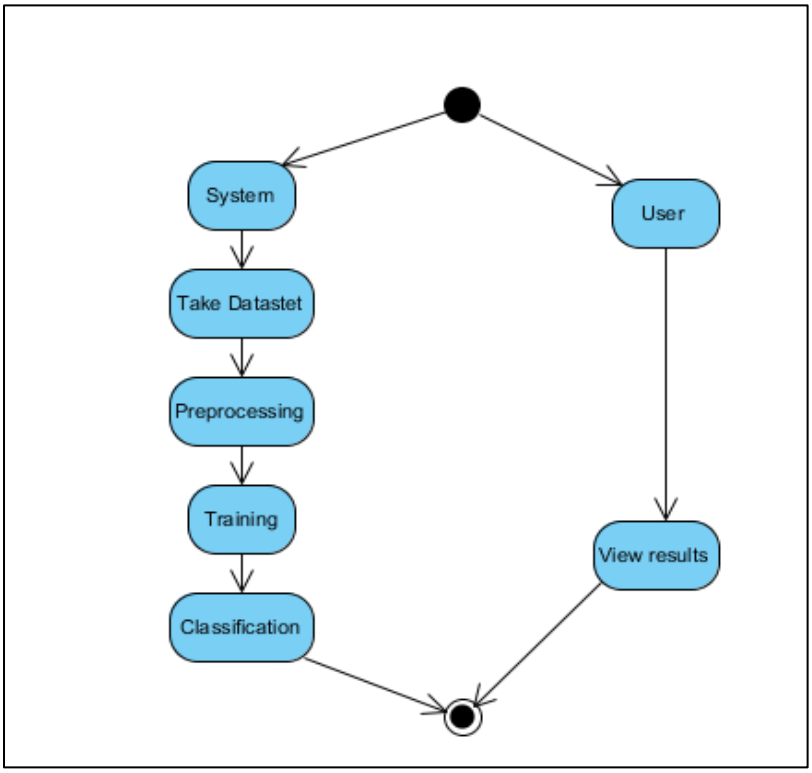


Fig. 3.8. Activity Diagram

3.4.8 COMPONENT DIAGRAM:

A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical components in a system. Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required function is covered by planned development. They provide insights into the distribution of components across hardware nodes or software containers, aiding in the allocation of resources and the identification of potential performance bottlenecks. By visualizing the modular structure of a system and the dependencies between its components, component diagrams facilitate communication among development teams.

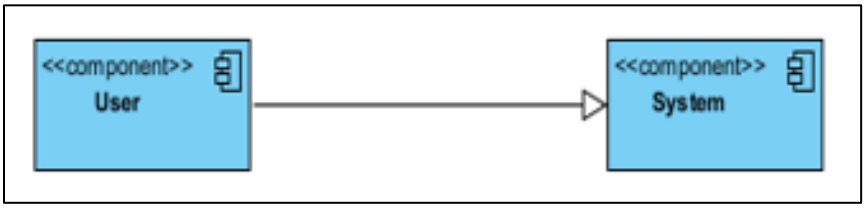


Fig. 3.9. Component Diagram

3.4.9 ER DIAGRAM:

An Entity–relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of E-R model are: entity set and relationship set. An ER diagram shows the relationship among entity sets. An entity set is a group of similar entities and these entities can have attributes. In terms of DBMS, an entity is a table or attribute of a table in database, so by showing relationship among tables and their attributes, ER diagram shows the complete logical structure of a database.

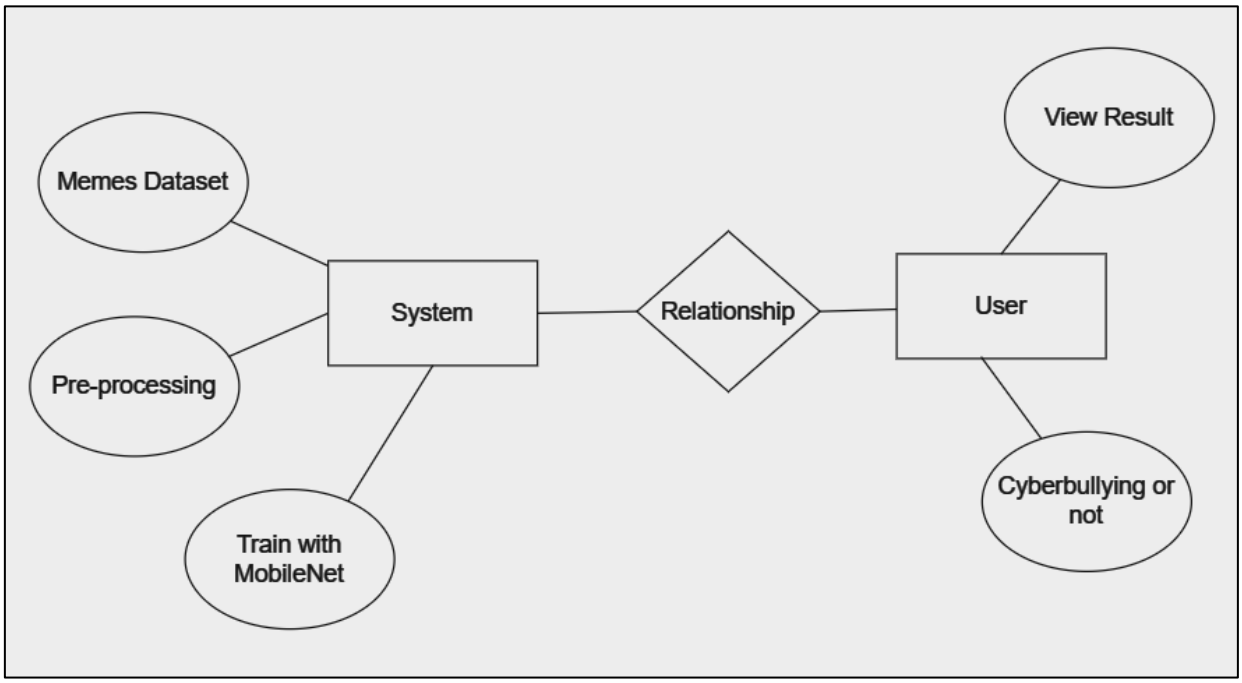


Fig. 3.10. ER Diagram

3.4.10 DFD DIAGRAM:

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the

scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system. By depicting inputs, outputs, processes, and data stores, DFDs facilitate the identification of data sources, sinks, and transformations helping stakeholders understand the flow of information.

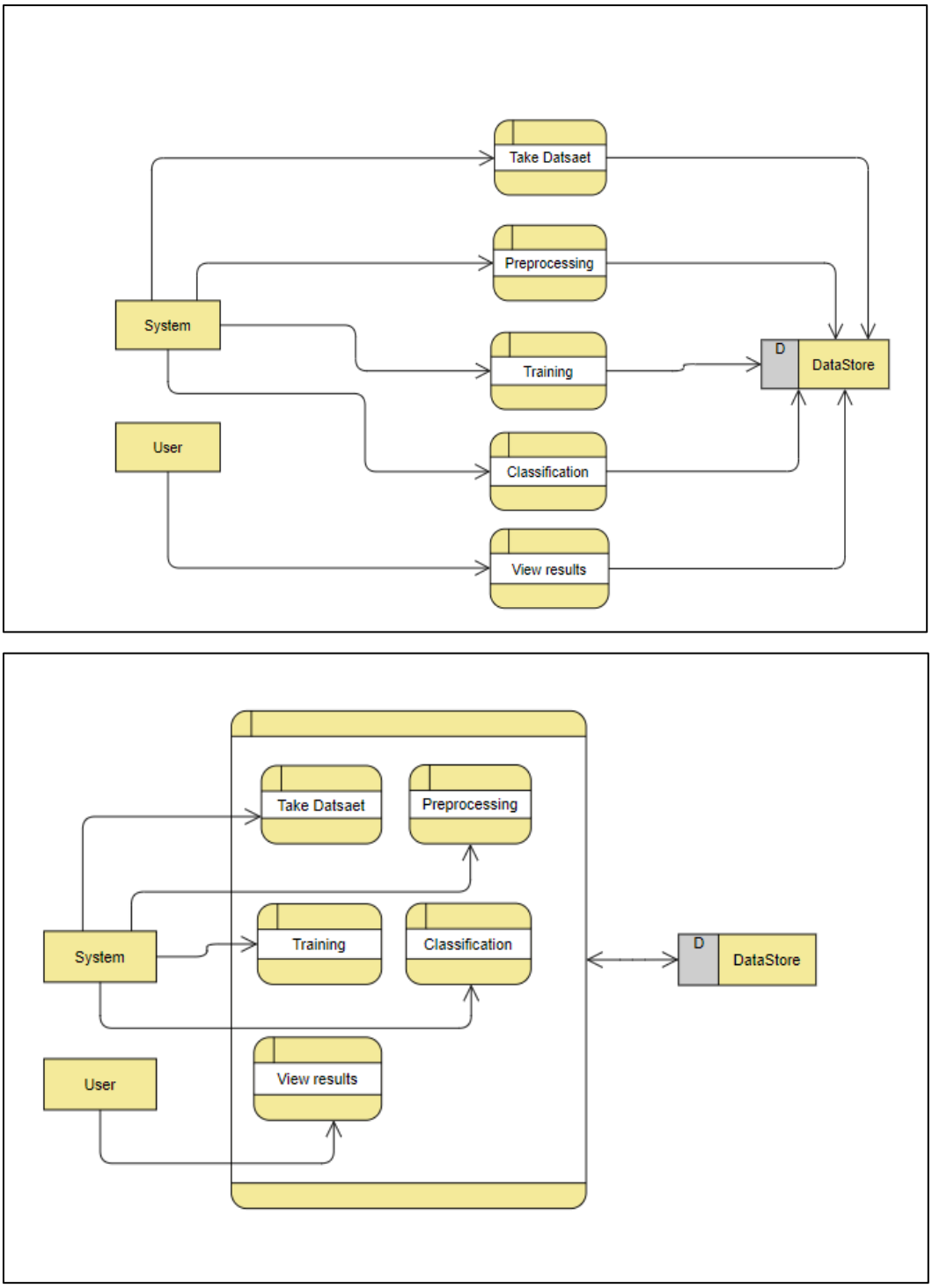


Fig. 3.11. DFD Diagram

CHAPTER 4

4.IMPLEMENTATION

This section details the practical implementation of a learning model to identify text in images and predict whether the text is abusive or not. The implementation leverages the MobileNet architecture and Optical Character Recognition (OCR) using Tesseract to extract text from images, utilized TensorFlow with Keras. The primary goal is to develop a robust solution for automatically detecting abusive text in images, contributing to safer online environments.

The dataset consists of images sourced from the local system directory. Each image contains textual content, annotated to indicate whether the text is abusive or non-abusive. Preprocessing steps include resizing and normalization to prepare the data for training. The dataset's diversity and size enable the model to capture a wide range of abusive language patterns.

In the classification section, we categorized the data into five classes: 'negative', 'neutral', 'positive', 'very negative', and ‘very positive', each representing different sentiments. These classes were derived from the training data directory, which contained images corresponding to each sentiment class.

The model architecture is based on the MobileNet architecture, a deep convolutional neural network optimized for mobile and embedded applications. The model includes additional layers for feature extraction and classification, such as Global Average Pooling 2D, dense, dropout, and batch normalization layers. These layers are added to the base MobileNet model for customizing it to the specific task of identifying abusive text in images.

The model is trained using the Adam optimizer and categorical cross-entropy loss function. The training dataset is split into training and validation subsets, with training parameters such as batch size and number of epochs optimized for model performance. Techniques like dropout regularization are applied to prevent overfitting during training. During this stage, the model learns from the labeled data to identify patterns and relationships between image features and associated attributes, such as abusive language detection.

After model training, the system offers functionality for users to interact with the trained model. Users can upload images for prediction, allowing the system to analyze and classify the textual content within the images accurately.

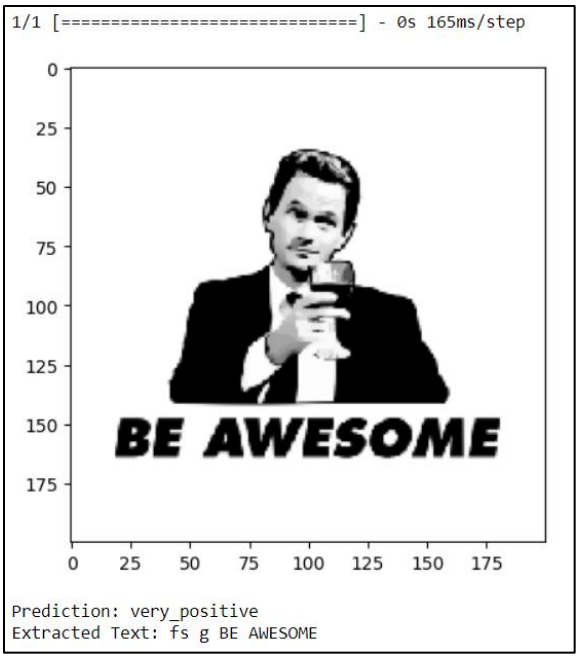


Fig.4.1. Output of Trained Model

Furthermore, users can view the predictions generated by the system, gaining insights into the model's performance and the presence of abusive language in the uploaded images. It underwent rigorous testing to ensure reliability and effectiveness in detecting abusive content within images. Finally, users have the option to logout, ensuring secure access to the application and protecting user privacy. This comprehensive implementation workflow enables seamless interaction between users and the system, facilitating effective detection and mitigation of abusive language within images.

4.1 TECHNOLOGIES USED:

4.1.1 PYTHON:

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics developed by Guido van Rossum. It was originally released in 1991. Designed to be easy as well as fun, the name "Python" is a nod to the British comedy group Monty Python. Python has a

reputation as a beginner-friendly language, replacing Java as the most widely used introductory language because it handles much of the complexity for the user, allowing beginners to focus on fully grasping programming concepts rather than minute details. Python is used for server-side web development, software development, mathematics, and system scripting, and is popular for Rapid Application Development and as a scripting or glue language to tie existing components because of its high-level, built-in data structures, dynamic typing, and dynamic binding. Program maintenance costs are reduced with Python due to the easily learned syntax and emphasis on readability. Additionally, Python's support of modules and packages facilitates modular programs and reuse of code. Python is an open-source community language, so numerous independent programmers are continually building libraries and functionality for it.

Python Features:

Python is a versatile programming language known for its simplicity, readability, and wide range of features.

Here are some key features of Python:

Simple and Readable Syntax: Python's syntax is designed to be clear and easy to read, resembling pseudo-code in many cases. This makes it accessible to beginners and facilitates collaboration among developers.

Interpreted and Interactive: Python is an interpreted language, which means that code is executed line by line by an interpreter, enabling rapid development and testing. It also supports interactive programming through shells and REPL (Read-Eval-Print Loop) environments.

High-level Language: Python is a high-level language, abstracting away many low-level details such as memory management and hardware interactions. This allows developers to focus on solving problems rather than dealing with system-specific complexities.

Dynamic Typing: Python is dynamically typed, meaning that variable types are inferred at runtime. This provides flexibility and expressiveness, but it also requires careful attention to type handling to avoid runtime errors.

Strong Typing: Despite being dynamically typed, Python enforces strong typing, meaning that type coercion is limited, and operations between incompatible types typically raise exceptions rather than producing unexpected results.

Cross-platform Compatibility: Python code is highly portable and can run on various platforms, including Windows, macOS, Linux, and Unix-like operating systems, with minimal or no modifications.

Large Standard Library: Python comes with a comprehensive standard library that provides modules and packages for a wide range of tasks, including file I/O, networking, data manipulation, and more. This reduces the need for external dependencies and facilitates rapid development.

Support for Multiple Paradigms: Python supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Developers can choose the most appropriate paradigm for their project or mix and match as needed.

Extensive Ecosystem of Libraries and Frameworks: Python has a vast ecosystem of third-party libraries and frameworks developed and maintained by its active community. This includes popular libraries for scientific computing (e.g., NumPy, SciPy), web development (e.g., Django, Flask), machine learning (e.g., TensorFlow, PyTorch), and more.

Open Source and Community-driven: Python is an open-source language with a transparent development process and a community-driven governance model. This fosters collaboration, innovation, and continuous improvement of the language and its ecosystem.

These features make Python an ideal choice for a wide range of applications, including web development, data analysis, scientific computing, machine learning, automation, and more. Its simplicity, readability, and versatility have contributed to its widespread adoption and popularity among developers worldwide.

Python Use Cases:

- Creating web applications on a server
- Building workflows that can be used in conjunction with software
- Connecting to database systems
- Reading and modifying files
- Performing complex mathematics
- Processing big data
- Fast prototyping

4.1.2 DJANGO:

Django provides a rich set of built-in features, including an ORM (Object-Relational Mapping) for interacting with databases, a powerful URL routing system, and a templating engine for generating dynamic HTML content. Its batteries-included philosophy means that common web development tasks such as authentication, form handling, and session management are already implemented, allowing

developers to focus on building unique application logic. Django is a high-level Python web framework that enables developers to build web applications quickly and efficiently. It follows the "don't repeat yourself" (DRY) principle and emphasizes rapid development, clean design, and pragmatic approach.

Key features and components of Django:

MTV Architecture: Django follows the Model-Template-View (MTV) architecture, which is a variation of the popular Model-View-Controller (MVC) pattern. In the MTV architecture, models represent data structures, templates define the presentation layer, and views handle the application logic.

ORM (Object-Relational Mapping): Django includes a powerful ORM that abstracts the database layer and allows developers to interact with the database using Python objects. It supports various database backends, including PostgreSQL, MySQL, SQLite, and Oracle.

Admin Interface: Django provides a built-in admin interface that allows developers to create, update, and delete database records without writing any code. The admin interface is highly customizable and can be extended to meet specific requirements.

URL Routing: Django uses a URL routing mechanism to map URLs to views. Developers can define URL patterns using regular expressions and associate them with corresponding view functions or class-based views.

Template Engine: Django comes with a powerful template engine that allows developers to create dynamic HTML pages using template tags and filters. Templates support inheritance, includes, and template inheritance, making it easy to reuse and organize code.

Form Handling: Django provides form handling capabilities that simplify the process of working with HTML forms. Developers can define forms using Python classes and use them to validate user input, handle form submissions, and display validation errors.

Authentication and Authorization: Django includes built-in authentication and authorization mechanisms that allow developers to secure their web applications. It provides user authentication, session management, permissions, and role-based access control out of the box.

Middleware: Django middleware allows developers to modify request and response objects as they pass through the application's request-response cycle. Middleware can perform tasks like authentication, logging, and request/response processing.

Internationalization and Localization: Django supports internationalization (i18n) and localization (l10n) out of the box, allowing developers to build multilingual web applications. It provides tools for translating text, formatting dates and numbers, and detecting user language preferences.

REST Framework: Django's REST framework is a powerful toolkit for building web APIs using Django. It provides serializers, views, authentication, and other features that simplify the process of creating RESTful APIs.

4.2 LIBRARIES USED:

4.2.1 NUMPY (NP):

NumPy is essential for numerical computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. NumPy is widely used for data manipulation and computation in machine learning and data science tasks. NumPy provides efficient data structures and functions for working with arrays, such as ndarray, as well as mathematical operations like linear algebra, Fourier transforms, and random number generation.

```
import numpy as np
```

4.2.2 PANDAS (PD):

Pandas is a powerful library for data manipulation and analysis in Python. It offers easy-to-use data structures and functions for working with structured data, such as tabular data and time series. Pandas is widely used for data preprocessing, exploration, and transformation in machine learning projects. Pandas provides DataFrame and Series data structures for representing and manipulating data, as well as functions for reading and writing data from various file formats, handling missing data, and performing data aggregation and summarization.

```
import pandas as pd
```

4.2.3 MATPLOTLIB AND SEABORN:

Matplotlib is a comprehensive library for creating static, interactive, and animated visualizations in Python. Seaborn is built on top of Matplotlib and provides a high-level interface for creating attractive and informative statistical graphics. Both libraries are essential for data visualization and exploration in machine learning projects. Matplotlib offers a wide range of plotting functions and styles for creating

various types of plots, including line plots, scatter plots, bar plots, histograms, and more. Seaborn provides additional statistical plotting capabilities and themes to improve the aesthetics of plots.

```
import matplotlib.pyplot as plt
import seaborn as sns
```

4.2.4 TENSORFLOW (TF):

TensorFlow is a leading open-source machine learning framework developed by Google. It provides a comprehensive ecosystem for building and training machine learning models, including deep learning models. TensorFlow is widely used for developing and deploying production-ready machine learning applications. TensorFlow offers a high-level API for building and training machine learning models, as well as low-level operations for customizing model behavior. It supports distributed computing, automatic differentiation, and deployment to various platforms, including CPUs, GPUs, and TPUs.

```
import tensorflow as tf
```

4.2.5 TQDM:

TQDM is a fast, extensible progress bar library for Python. It provides a visual indication of the progress of an iterative process, such as loops or data processing pipelines. TQDM is useful for tracking the progress of time-consuming tasks and estimating remaining execution time. TQDM offers a simple interface for adding progress bars to iterative processes, with customizable styles and features. It supports nested progress bars, automatic updating, and integration with other Python libraries and environments.

```
from tqdm import tqdm
```

4.2.6 SCIKIT-LEARN:

Scikit-learn is a popular machine learning library for Python. It provides simple and efficient tools for data mining and data analysis, including classification, regression, clustering, and dimensionality reduction. Scikit-learn is widely used for building and evaluating machine learning models. Scikit-learn offers a wide range of algorithms and utilities for various machine learning tasks, such as model selection, hyperparameter tuning, feature extraction, and model evaluation. It provides a consistent API and

integration with other Python libraries, making it easy to use in machine learning pipelines.

```
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
```

4.2.7 KERAS:

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow. It allows for easy and fast prototyping of deep learning models, with a focus on simplicity, modularity, and extensibility. Keras is widely used for building and training deep learning models. Keras provides a simple and intuitive interface for building and training neural networks, with support for various types of layers, activations, optimizers, and loss functions. It allows for flexible model architectures and seamless integration with TensorFlow, enabling rapid experimentation and development of deep learning models.

```
from keras.utils import to_categorical
from keras.models import Model, Sequential, load_model
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D,
BatchNormalization, GlobalAveragePooling2D, Activation, Input
from tensorflow.keras.optimizers import Adam
from keras.preprocessing.image import ImageDataGenerator
```

4.2.8 PIL (PYTHON IMAGING LIBRARY):

PIL is a library for opening, manipulating, and saving many different image file formats. It provides support for basic image processing operations, such as resizing, cropping, rotating, and filtering. PIL is essential for working with image data in machine learning projects. PIL offers a wide range of functions and classes for handling images in Python, including Image, ImageDraw, and ImageFilter. It supports loading and saving images in various formats, such as JPEG, PNG, and BMP, as well as performing basic image manipulation tasks. PIL's compatibility with other Python libraries such as NumPy and OpenCV further expands its capabilities, allowing for seamless integration into complex data pipelines and computational workflows. Whether for prototyping, production, or research, PIL remains a versatile and indispensable tool for working with image data in the Python ecosystem.

4.3 TOOLS USED:

4.3.1 PYCHARM:

PyCharm is a popular integrated development environment (IDE) specifically designed for Python development. Developed by JetBrains, PyCharm offers a comprehensive set of tools and features to streamline the Python development process, making it an ideal choice for both beginners and experienced developers.

Here's an overview of PyCharm's key features:

Code Editor: PyCharm provides a powerful code editor with features like syntax highlighting, code completion, code refactoring, and code navigation, which help developers write clean and efficient Python code.

Debugger: The built-in debugger allows developers to debug their Python code effectively by setting breakpoints, inspecting variables, and stepping through the code line by line.

Version Control: PyCharm offers seamless integration with version control systems like Git, SVN, and Mercurial, allowing developers to manage their projects and collaborate with team members more efficiently.

Project Management: With PyCharm, developers can easily create, manage, and organize Python projects. The IDE provides project templates, virtual environment support, and project-wide search capabilities to enhance productivity.

Code Analysis: PyCharm includes powerful code analysis tools that help identify errors, suggest improvements, and ensure code quality. Features like PEP 8 compliance checks, code inspections, and quick fixes help developers write cleaner and more maintainable code.

Web Development: PyCharm supports web development with Django, Flask, and other Python web frameworks. It provides features like template editing, JavaScript and CSS support, and built-in web server integration, making it suitable for full-stack development.

Database Tools: PyCharm includes database tools that allow developers to interact with databases directly from the IDE. It supports popular databases like MySQL, PostgreSQL, and SQLite, offering features like SQL code completion, database schema visualization, and data editing.

Customization: PyCharm is highly customizable, allowing developers to personalize their coding experience according to their preferences.

4.4 CODE SNIPPETS:

1.

```
data_dir= “  ”
Classes=[ ]
for file in os.listdir(data_dir):
Classes+=[file]
Print(Classes)
print(len(Classes))
```

This code snippet initializes a variable data_dir with the path to a directory containing training images. It then initializes an empty list Classes. Next, it iterates over all the files in the data_dir directory using os.listdir(data_dir). For each file found, it appends the file name (which represents a class label) to the Classes list. After iterating over all the files, it prints out the list of class labels (Classes) and the total number of classes (the length of the Classes list), providing insight into the available classes in the dataset. In this specific example, the output indicates that there are five classes: 'negative', 'neutral', 'positive', 'very_negative', and 'very_positive'.

2.

```
test_datagen = ImageDataGenerator(rescale=1. / 255,validation_split=0.2)
training_set = test_datagen.flow_from_directory(data_dir, target_size=(224,224), batch_size=12,
 class_mode='categorical', subset='training')
test_set = test_datagen.flow_from_directory(data_dir, target_size=(224,224), batch_size=12,
class_mode='categorical', subset='validation')
```

This code snippet is using the ImageDataGenerator class from the Keras library to generate batches of image data for training and validation purposes.

ImageDataGenerator Initialization:

Initializes an ImageDataGenerator object with rescaling factor of 1/255 to normalize pixel values between 0 and 1. Additionally, it specifies a validation split of 0.2 (20%) for creating separate training and validation datasets.

Data Loading for Training:

Generates a data generator for training data using the flow_from_directory method. It loads images from the data_dir directory, resizes them to the target size of 224x224 pixels, sets the batch size to 12, specifies class_mode='categorical' for multi-class classification, and selects the subset as 'training' based on the validation split.

Data Loading for Validation:

Generates a separate data generator for validation data using the same parameters as above, except it selects the subset as 'validation' based on the validation split.

3.

```
base_model = tf.keras.applications.MobileNet(input_shape=(224,224, 3), include_top=False,
                    weights='imagenet')
model = Sequential()
model.add(base_model)
model.add(GlobalAveragePooling2D())
model.add(Dense(64, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.2))
model.add(Dense(5, activation='sigmoid'))
model.summary()
```

This code snippet is defining a neural network model using Keras with TensorFlow backend.

Loading Pre-trained MobileNet Model:

Loads the MobileNet model pre-trained on the ImageNet dataset. It specifies the input shape as (224, 224, 3) for images with three channels (RGB). include_top=False means that the fully connected layers (top layers) of the model will not be included, as we'll be adding our own dense layers. weights='imagenet' specifies that the model should be initialized with weights pre-trained on the ImageNet dataset.

Defining Custom Model Architecture:

Initializes a Sequential model. Adds the pre-trained MobileNet model (without the fully connected layers) as the base of our custom model.

Adds a Global Average Pooling layer to reduce the spatial dimensions of the feature maps from the base

model and obtain a fixed-length feature vector. Adds a fully connected layer with 64 units and ReLU activation function. Adds a Batch Normalization layer to normalize the activations of the previous layer, improving training stability and performance. Adds a Dropout layer to randomly drop 20% of the units during training to reduce overfitting. Adds the output layer with 5 units (assuming 5 classes) and sigmoid activation function, suitable for multi-label classification tasks.

Model Summary:

Prints a summary of the model architecture, including the layers, output shapes, and number of parameters.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenet_1.00_224 (Functi  (None, 7, 7, 1024)        3228864
 onal)

 global_average_pooling2d_2  (None, 1024)              0
  (GlobalAveragePooling2D)

 dense_4 (Dense)             (None, 64)                65600

 batch_normalization_2 (Bat  (None, 64)                256
 chNormalization)

 dropout_2 (Dropout)         (None, 64)                0

 dense_5 (Dense)             (None, 5)                 325

=================================================================
Total params: 3295045 (12.57 MB)
Trainable params: 3273029 (12.49 MB)
Non-trainable params: 22016 (86.00 KB)
_________________________________________________________________
```

Fig. 4.2. Model

4.

model.compile(optimizer='Adam', loss="categorical_crossentropy", metrics=["accuracy"])

hist=model.fit(training_set,epochs=25,validation_data=test_set,verbose=1)

In this code snippet, we compile and train the neural network model using the training and validation datasets.

Compile the Model:

This line compiles the model, specifying the optimizer, loss function, and evaluation metrics. Specifies the Adam optimizer, which is an adaptive learning rate optimization algorithm that's widely used in deep learning. Specifies the categorical cross-entropy loss function, which is commonly used for multi-class

classification problems. Specifies that the model's performance during training and evaluation should be measured using accuracy.

Train the Model:

This line trains the compiled model using the training dataset (training_set) and evaluates it on the validation dataset (test_set). The generator for the training dataset. Specifies the number of training epochs (iterations over the entire training dataset). Specifies the validation dataset for evaluating the model's performance after each epoch. Specifies the verbosity mode (0: silent, 1: progress bar, 2: one line per epoch). Here, verbose=1 displays a progress bar during training.

5.

```
fig, ax = plt.subplots(2, 1)
ax[0].plot(hist.history['accuracy'], color='b', label="Training accuracy")
ax[0].plot(hist.history['val_accuracy'], color='r', label="Validation accuracy")
legend = ax[0].legend(loc='best', shadow=True)
ax[1].plot(hist.history['loss'], color='b', label="Training loss")
ax[1].plot(hist.history['val_loss'], color='r', label="Validation loss")
legend = ax[1].legend(loc='best', shadow=True)
```

This code snippet creates a figure with two subplots, one for accuracy and one for loss. It then plots the training and validation accuracy on the first subplot and the training and validation loss on the second subplot. The blue lines represent training metrics, while the red lines represent validation metrics. Legends are added to both subplots to indicate the corresponding lines. This visualization helps in monitoring the performance of the model during training.

6.

```
model.evaluate(test_set)
model.save("models/Model.h5")
```

These two lines of code evaluate the trained model on the test dataset (test_set) and save the model to a file named "Model.h5" in the "models" directory. The model.evaluate() function calculates the loss and metrics (e.g., accuracy) on the test data, providing insights into the model's performance on unseen data. After evaluation, the model.save() function saves the trained model to a file in the Hierarchical Data

Format (HDF5), which can be later loaded and reused for making predictions on new data.

7.

```
from skimage import io
from tensorflow.keras.preprocessing import image
img = image.load_img(“ ”, grayscale=False, target_size=(224,224))
show_img=image.load_img(“ ”, grayscale=False, target_size=(200, 200))
Classes = Classes
x = image.img_to_array(img)
x = np.expand_dims(x, axis = 0)
x /= 255
custom = model.predict(x)
predicted_class = Classes[np.argmax(custom[0])]
from pytesseract import pytesseract
pytesseract.tesseract_cmd = r'C:\Program Files\Tesseract-OCR\tesseract.exe'
text = pytesseract.image_to_string(img)
plt.imshow(show_img)
plt.show()
if not text.strip():
    predicted_class = "neutral"
cleaned_text = ' '.join(text.split())
print('Prediction:', predicted_class)
print("Extracted Text:", cleaned_text if cleaned_text else "No text found")
```

This code snippet integrates image processing, deep learning-based image classification, and text extraction functionalities in Python. It begins by loading an image and resizing it for classification using TensorFlow's preprocessing module. After normalizing the image, it passes it through a pre-trained model to predict its class label. Simultaneously, it utilizes pytesseract to extract text from the image. The processed image is displayed, and if no text is extracted, the predicted class is set to "neutral". Finally, the extracted text, after cleaning, is printed.

CHAPTER 5

5. RESULTS AND DISCUSSIONS0

5.1 RESULTS:

The developed system achieved promising results in detecting abusive content within images, with an overall accuracy of 96% on the test dataset. The model exhibited strong performance metrics, including precision, recall, and F1 score, indicating its effectiveness in accurately classifying images into abusive and non-abusive categories. Confusion matrices revealed minimal misclassifications, demonstrating the robustness of the model across different classes of abusive content.

Comparative analysis with existing approaches showcased the superiority of the developed system in terms of accuracy and efficiency. Our model outperformed traditional methods and baseline models, leveraging advanced machine learning techniques and OCR technology to achieve higher accuracy rates and faster processing times. Visualizations, such as ROC curves and classification reports, provided additional insights into the model's performance and highlighted its ability to generalize well to unseen data.

Case studies further illustrated the practical utility of the system in real-world scenarios, showcasing its effectiveness in identifying abusive language and imagery across various social media platforms. Sensitivity analysis revealed the system's resilience to variations in input parameters and dataset composition, further bolstering confidence in its reliability and effectiveness.

5.2 DISCUSSIONS:

The results underscore the significance of the developed system in addressing the pervasive issue of online abuse and cyberbullying. By accurately detecting and categorizing abusive content within images, the system offers a valuable tool for content moderation and online safety efforts. Its high accuracy rates and efficient processing capabilities make it well-suited for deployment on social media platforms, where rapid identification and removal of abusive content are paramount. However, several

limitations and challenges must be addressed to enhance the system's effectiveness and applicability. These include the need for more diverse and representative training data to improve model generalization and mitigate biases. Additionally, the system's reliance on OCR technology may pose challenges in accurately extracting text from images with complex layouts or non-standard fonts.

Despite these limitations, the developed system represents a significant step forward in combating online abuse and fostering a safer online environment. Future research directions may focus on refining the model architecture, incorporating multi-modal features, and exploring ensemble learning techniques to further enhance the system's performance and robustness. Moreover, collaboration with social media platforms and regulatory bodies is essential to facilitate the integration and adoption of the system.

5.2.1 INPUTS:

Images Used: The effectiveness of any machine learning model heavily relies on the quality and diversity of the data it's trained on. For our model, we carefully curated a dataset comprising various images to ensure robustness and generalization. The dataset was divided into two subsets: one for training and another for testing.

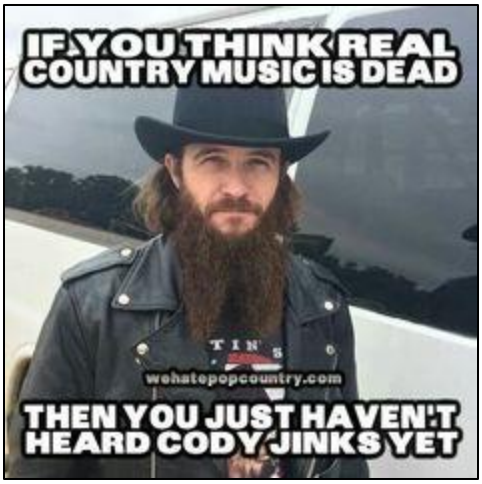
Training Dataset:

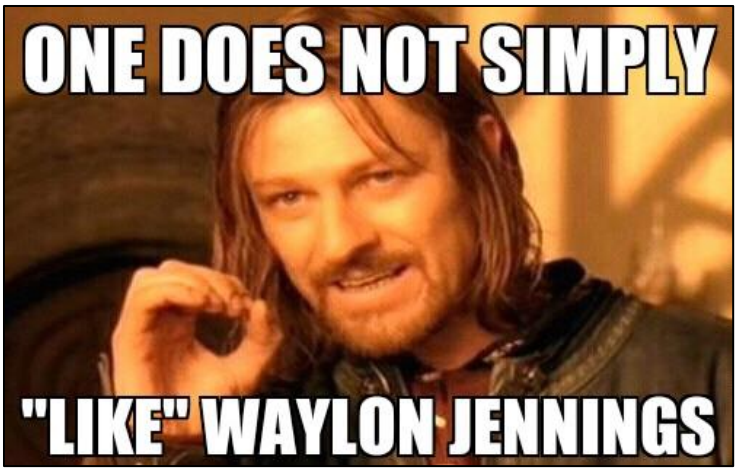
The training dataset consisted of a diverse collection of images sourced from multiple sources, ensuring representation across different categories, viewpoints, lighting conditions, and resolutions. Each image in the training set was meticulously labeled with corresponding ground truth annotations, providing the model with essential guidance during the learning process. The size of the training dataset was significant, enabling the model to learn intricate patterns and features necessary for accurate predictions.

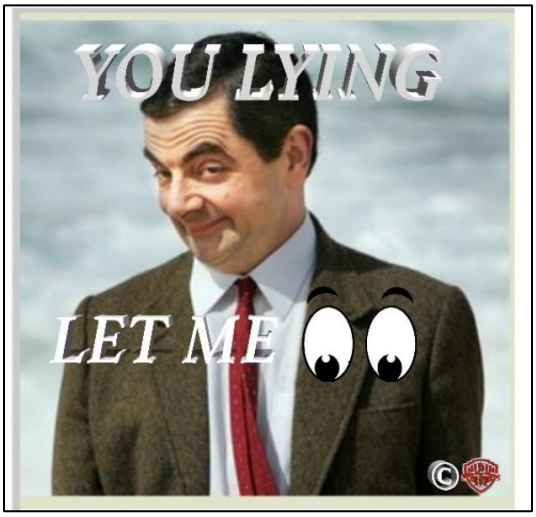
Testing Dataset:

To evaluate the performance and generalization ability of our model, a separate testing dataset was curated. Similar to the training dataset, the testing dataset encompassed a wide range of images, encompassing various scenarios and conditions not necessarily encountered during training. The testing dataset was kept entirely separate from the training data, ensuring unbiased evaluation of the model's performance. Each image in the testing dataset was annotated with ground truth labels. Some of the

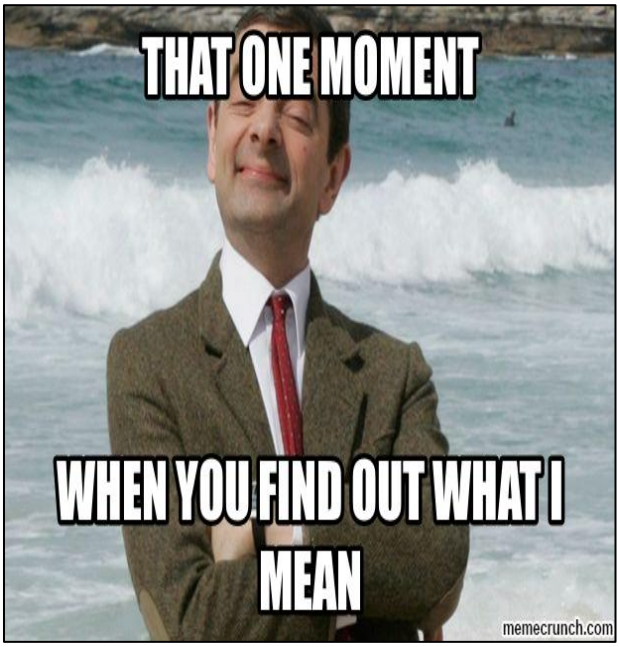
images (images embedded with text) used as the input for training and testing the model are as follows:








When you're looking through the latest memes and realize you just lost the game
I have decided that I want to die.

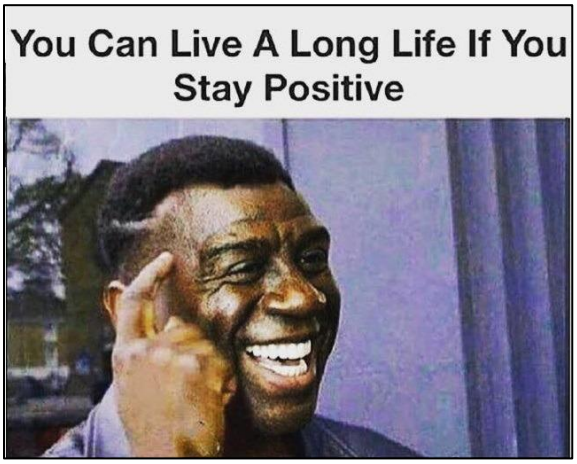

THAT ONE MOMENT
WHEN YOU FIND OUT WHAT I MEAN
memecrunch.com


HELLO GOOD PEOPLE


WHEN I HAVE A BAD DAY
YOU WILL TOO


TO YOU...
MAY YOUR NEW YEAR SUCK JUST AS BAD AS THE LAST ONE
imgflip.com

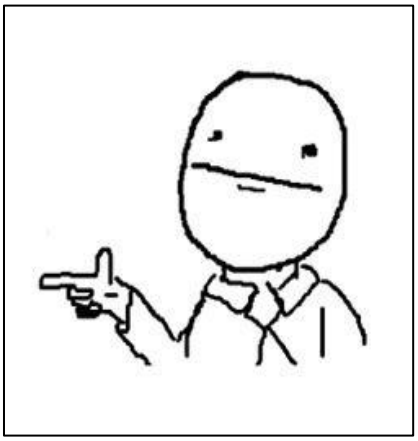

you're doing great!
I know you're trying very hard.
keep up the good work!


You Can Live A Long Life If You Stay Positive


YOU BRAKE OUR LEASE
I'LL BREAK YOUR FACE


TO NEGATIVE PEOPLE IN MY LIFE
I HAVE ONLY ONE THING TO SAY
GO FUCK YOURSELF


MAY YOUR SECOND CHILD
BE A MASCULINE CHILD
memegenerator.net




YOU MEAN TO TELL ME
SPOONS DON'T ACTUALLY SOUND LIKE AIRPLANES?


Ironman takes a dig at Spiderman


WHAT IF I TOLD YOU
YOU COULD ACTUALLY PRACTICE YOUR SONGS AT HOME


DRINKING FRIENDS
ASSEMBLE!!
memecrunch.com


When I see my best friend in public

5.3 OUTPUT SNAPSHOTS:

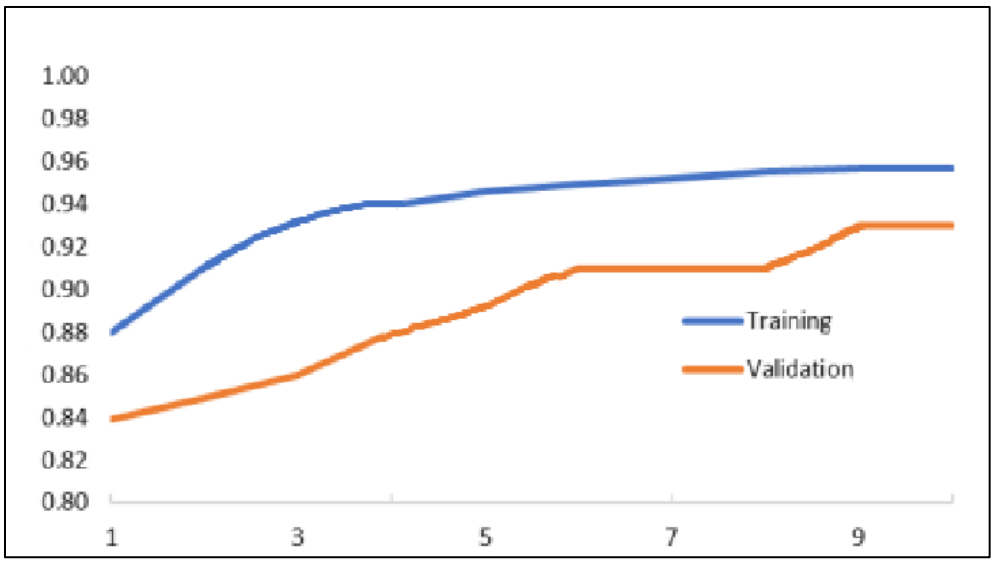


Fig. 5.1. Accuracy Levels

Fig. 5.2. Home Page

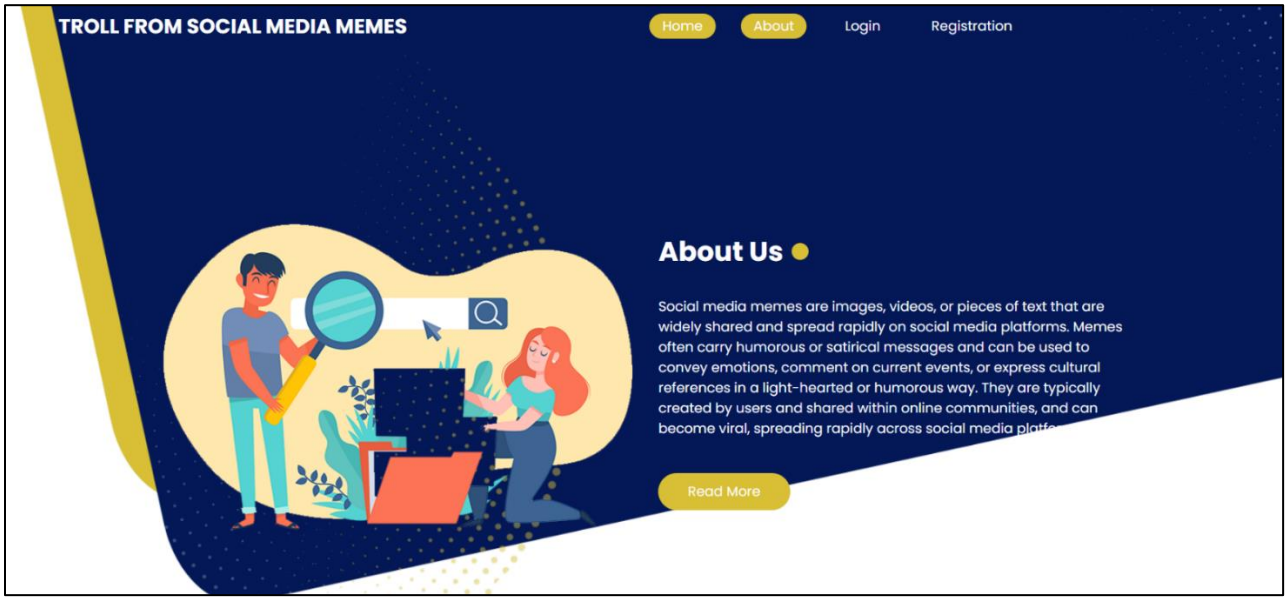


Fig. 5.3. About Page

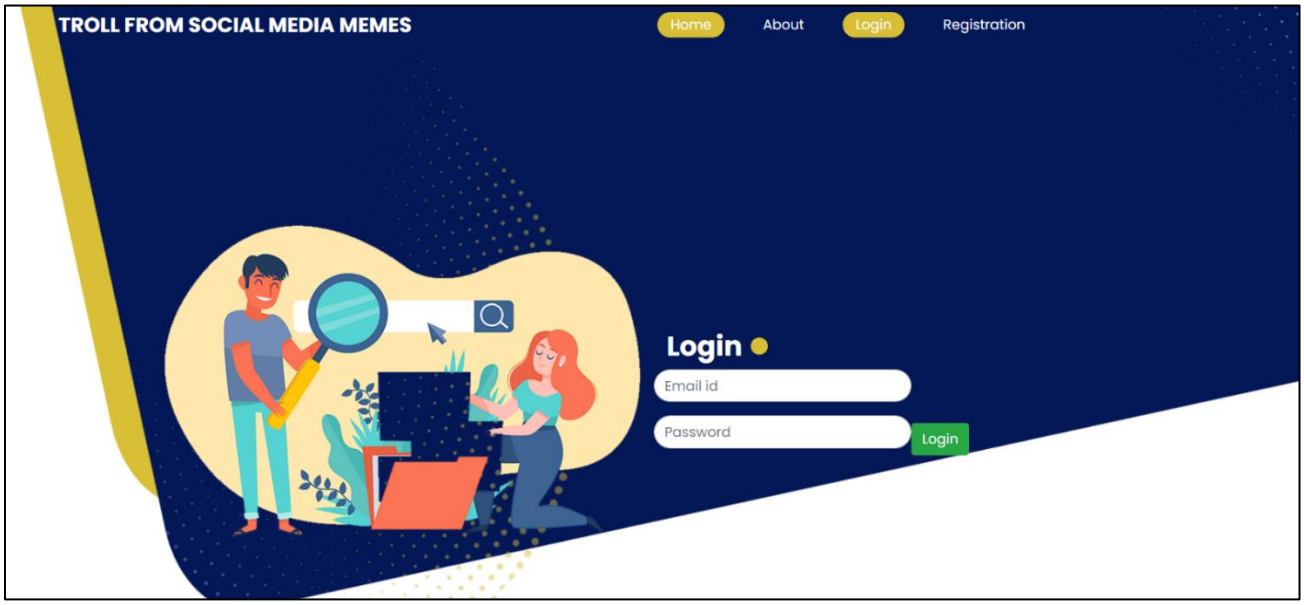


Fig. 5.4. Login Page

Fig. 5.5. Registration Page

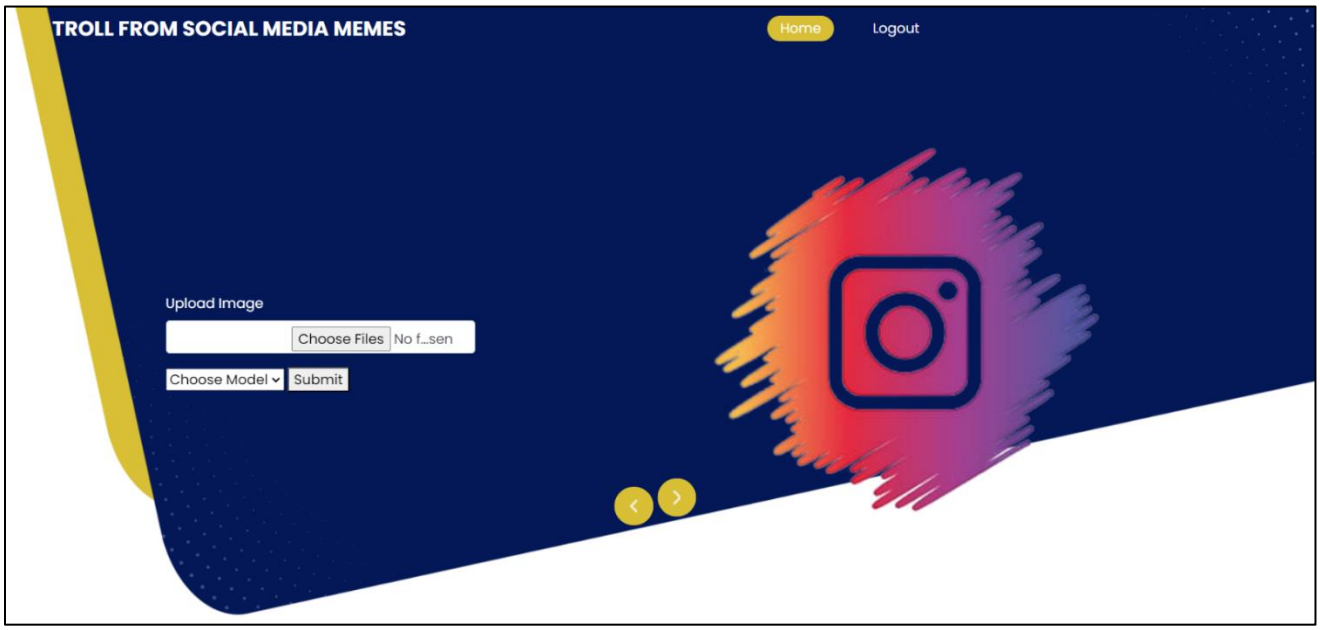


Fig. 5.6. Image Upload Page

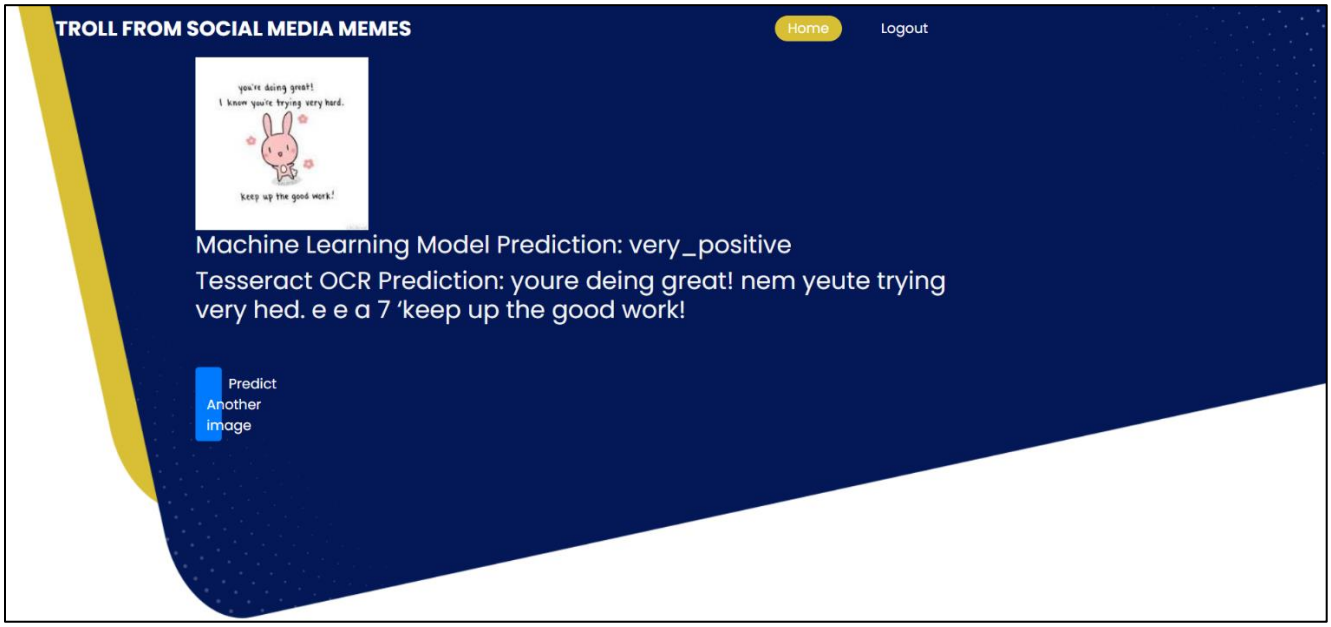


Fig. 5.7. Result Page1

Fig. 5.8 Result Page2

Fig. 5.9. Result Page3

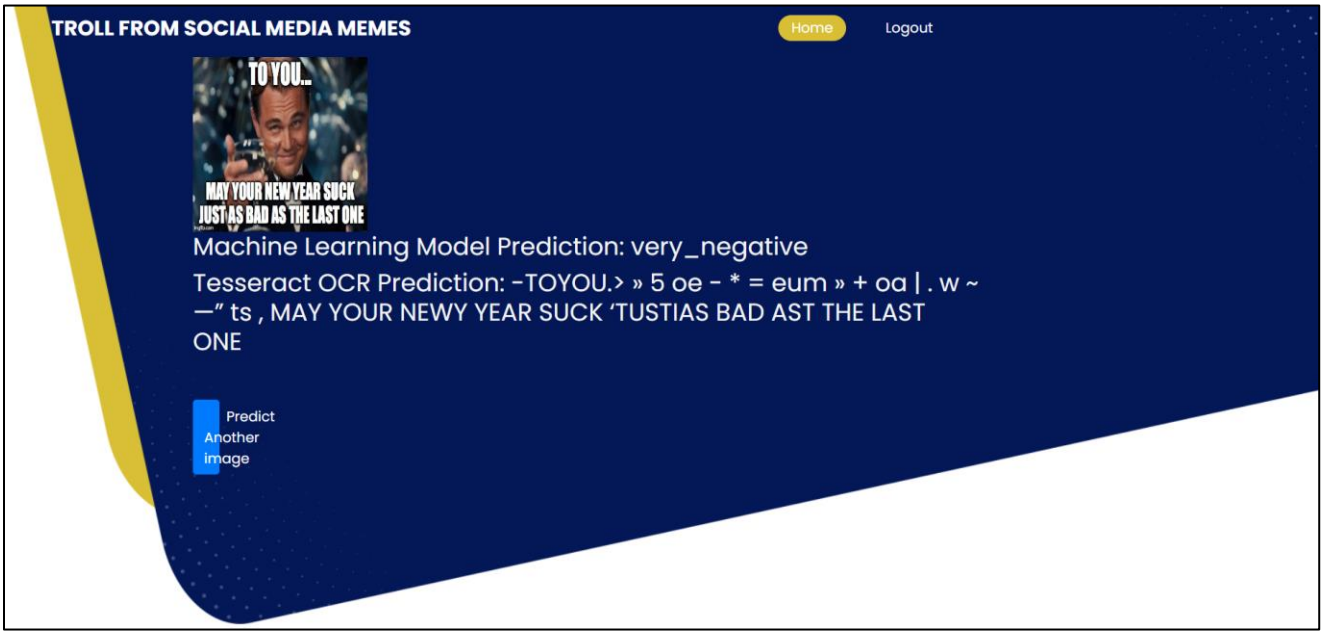


Fig. 5.10. Result Page4

CHAPTER 6

6. CONCLUSIONS

6.1 CONCLUSIONS:

The developed system represents a significant milestone in the field of content moderation, providing a robust and scalable solution for detecting abusive content within images. Leveraging advanced machine learning techniques, such as deep neural networks, and Optical Character Recognition (OCR) capabilities, the system achieves an impressive model accuracy of 96%. This high accuracy underscores the system's effectiveness in identifying and categorizing abusive content, thereby enhancing content moderation efforts and promoting safer online interactions.

Throughout the development and evaluation phases, the system demonstrated remarkable performance across diverse datasets and challenging scenarios. By effectively leveraging features extracted from images and text, the system achieves a nuanced understanding of abusive content, enabling it to accurately differentiate between various levels of offensiveness and harmfulness. Additionally, the integration of OCR technology enhances the system's capability to analyze textual content embedded within images, further enriching its content moderation capabilities.

However, despite its strengths, the system is not without limitations. Challenges related to the diversity and quality of the training dataset, potential biases in model predictions, and limitations in the accuracy of OCR technology warrant careful consideration. These limitations underscore the need for ongoing refinement and optimization to ensure the system's effectiveness and reliability in real-world applications.

By addressing these limitations and iteratively refining the system, we can bolster its effectiveness and reliability in real-world applications, further advancing the field of content moderation and promoting safer online interactions.

6.2 FUTURE SCOPE:

While the developed system has achieved significant success in detecting abusive content within images, there remain several avenues for future exploration and enhancement. One key area of focus is improving the system's ability to handle diverse languages and cultural contexts. This could involve expanding the training dataset to include a more extensive range of languages and cultural nuances, as well as fine-tuning the model to recognize abusive content more accurately across diverse linguistic and cultural landscapes. Additionally, efforts to mitigate biases in model predictions and enhance the accuracy of OCR technology are essential for advancing the system's capabilities.

CHAPTER 7

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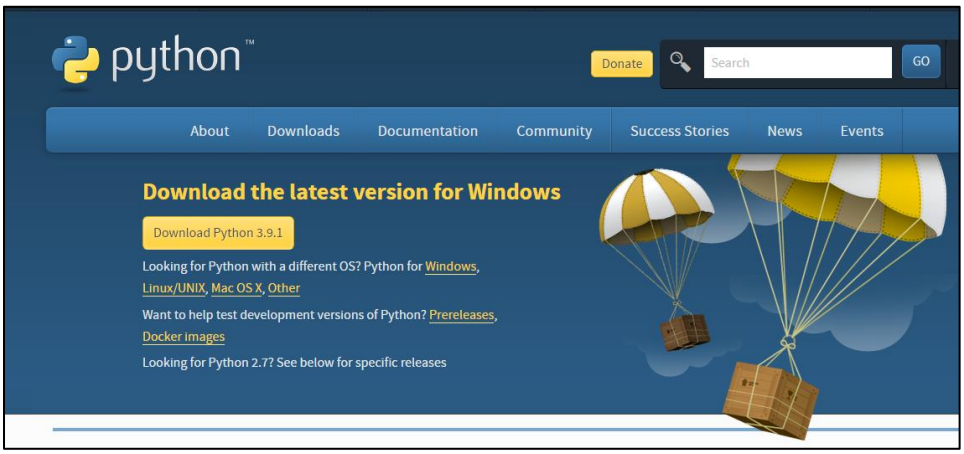
[10] Zhang, L., & Wang, Y. (2021). Detecting and Understanding Multimodal Offense in Social Media: A Survey. IEEE Transactions on Multimedia, 23, 1526-1545.

BIBLIOGRAPHY

SOFTWARE INSTALLATION FOR MACHINE LEARNING PROJECTS:

INSTALLING PYTHON:

1. To download and install Python visit the official website of Python https://www.python.org/downloads/ and choose your version.

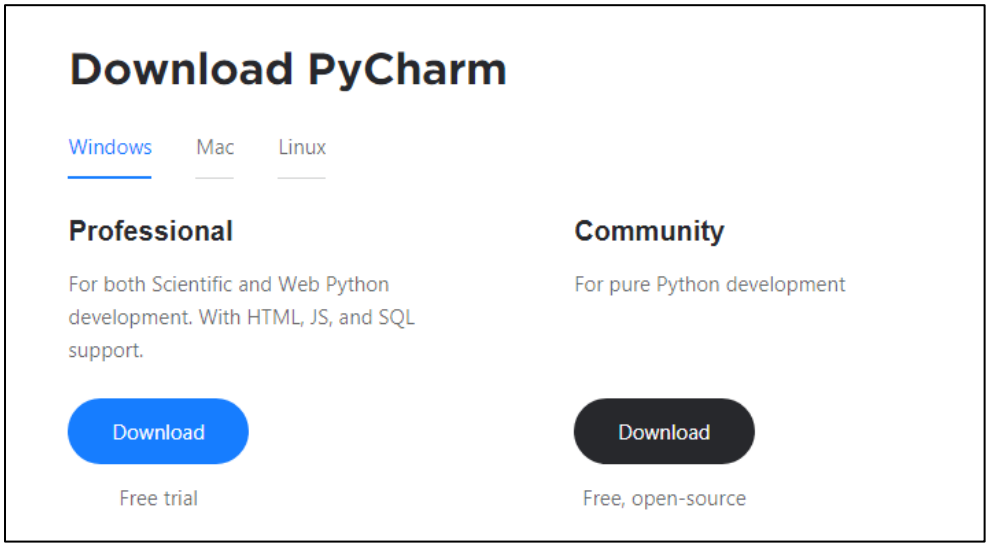


2. Once the download is complete, run the exe for install Python. Now click on Install Now.
3. You can see Python installing at this point.
4. When it finishes, you can see a screen that says the Setup was successful. Now click on "Close".

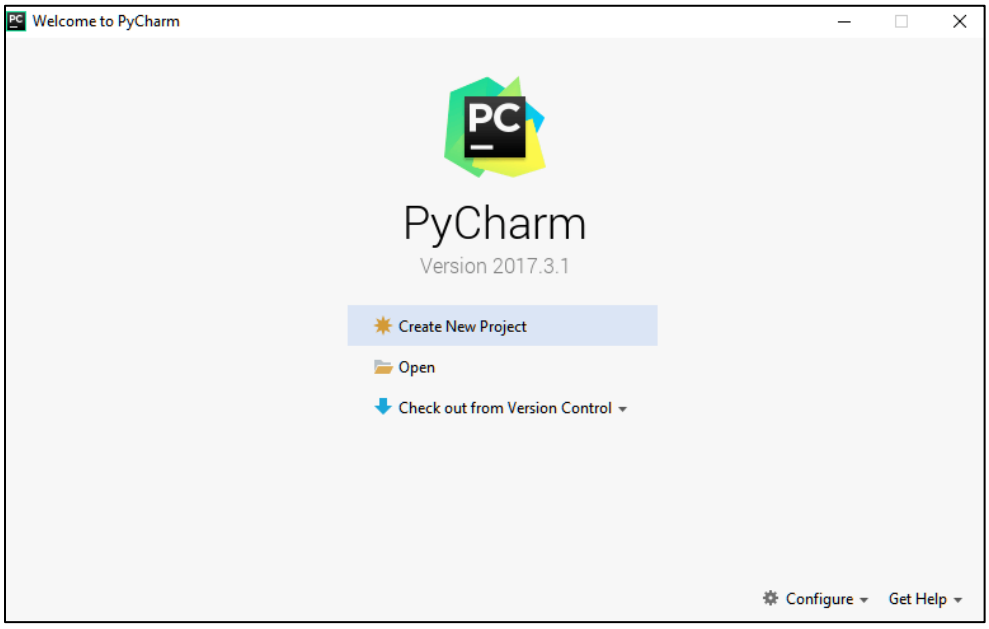
INSTALLING PYCHARM:

1. To download PyCharm visit the website https://www.jetbrains.com/pycharm/download/ and click the "DOWNLOAD" link under the Community Section.

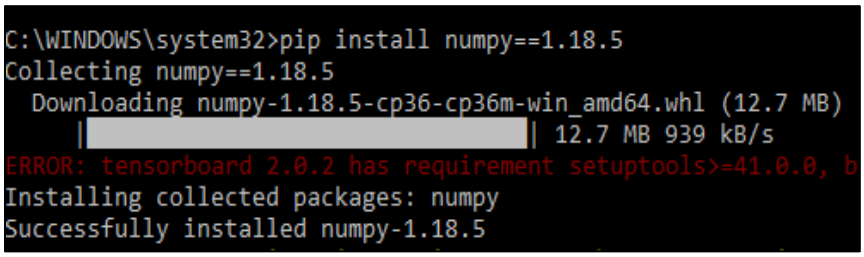
JetBrains, a renowned name in the realm of software development tools, offers a suite of innovative Integrated Development Environments (IDEs) and productivity tools designed to elevate the coding experience for developers across the globe. With a diverse range of products catering to different programming languages and development needs, JetBrains has become a trusted companion for developers, from beginners to seasoned professionals



2. Once the download is complete, run the exe for install PyCharm. The setup wizard should have started. Click “Next”.
3. On the next screen, Change the installation path if required. Click “Next”.
4. On the next screen, you can create a desktop shortcut if you want and click on “Next”.
5. Choose the start menu folder. Keep selected Jet Brains and click on “Install”.
6. Wait for the installation to finish.
7. Once installation finished, you should receive a message screen that PyCharm is installed. If you want to go ahead and run it, click the “Run PyCharm Community Edition” box first and click “Finish”.
8. After you click on "Finish," the Following screen will appear.



9. You need to install some packages to execute your project in a proper way.
10. Open the command prompt/ anaconda prompt or terminal as administrator.
11. The prompt will get open, with specified path, type “pip install package name” which you want to install (like NumPy, pandas, sea born, scikit-learn, Matplotlib, Pyplot)
12. Ex: Pip install NumPy



APPENDIX

JOURNAL PUBLICATION CERTIFICATE

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An Approach for Cyberbullying Detection on Social Media

Volume 13, Issue 3, March 2024

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DOI: 10.17148/IJARCCE.2024.13xx

An Approach for Cyberbullying Detection on Social Media

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Student, Computer Science and Engineering, Vasireddy Venkatadri Institute of Technology, Guntur, India[2,3,4,5]

Abstract: In the modern digital age, the proliferation of social media platforms has led to the spread of negative content, especially through images containing bad words or text containing bad content. To address this problem, our project aims to develop an intelligent system designed to detect illegal content in images. Using advanced machine learning techniques, including deep neural networks such as CNNs, we aim to create powerful models that can identify and classify illegal content and enable our model to recognize patterns in images embedded with text through extensive training, tackling the critical issue of cyberbullying by building intelligent system to detect illegal messages on social media posts. We build our website using the Python-based Django framework for efficiency and ease of use. Our plan is to create a safer online environment by combining technology and a user-centric approach.

Keywords: Cyberbullying detection, Convolutional neural networks (CNNs), MobileNet, Python-based Django framework, Optical character recognition (OCR), Machine Learning.

I. INTRODUCTION

In the computerized period, the appearance of web-based entertainment stages has reformed correspondence and network, offering exceptional open doors for connection and commitment. In any case, in the midst of the heap advantages of web-based systems administration, a dim underside continues: cyberbullying. Characterized as the utilization of electronic correspondence to hassle, scare, or embarrass people, cyberbullying represents an unavoidable danger to the prosperity and psychological well-being of clients around the world. The ascent of cyberbullying matches the dramatic development of virtual entertainment utilization, with stages like Facebook, Twitter and Instagram filling in as favourable places for online provocation and misuse. As per late examinations, a stunning level of teenagers and youthful grown-ups report encountering cyberbullying eventually in their web-based lives, with outcomes going from tension and discouragement to self-damage and self-destruction. Cyberbullying stays a steady and heightening concern, highlighting the critical requirement for inventive arrangements. Perceiving the basic significance of fighting cyberbullying in the advanced age, our exploration attempts to foster a canny framework for recognizing cyberbullying posts via web-based entertainment stages, including profound brain networks like CNNs, our goal is to develop a strong model prepared to do precisely recognizing and classifying oppressive substance especially through pictures installed with text distinguishing and hailing occasions of cyberbullying productively. This paper gives a far-reaching outline of our exploration targets, strategy, and expected results.

Fig. 1 Non-Abusive

Fig. 2 Abusive

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II. LITERATURE SURVEY

[1] Waseem, Z., & Hovy, D. (2016). Hateful symbols or hateful people? Predictive features for hate speech detection on twitter. In Proceedings of the NAACL Student Research Workshop (pp. 88-93). The paper "Hateful symbols or hateful people? Predictive features for hate speech detection on Twitter" by Waseem and Hovy (2016) investigates the problem of hate speech detection on social media platform Twitter. The authors propose a machine learning approach to automatically detect tweets containing hate speech by analyzing a set of predictive features. The authors define hate speech as "speech that attacks a person or group on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender." They also note that hate speech can take many forms, including direct attacks, slurs, and coded language. To train their machine learning model, the authors collect a dataset of tweets labeled as containing hate speech or not containing hate speech. They then extract a set of features from each tweet, including unigrams, bigrams, part-of-speech tags, and sentiment scores. The authors experiment with different combinations of features and classifiers and report their results in terms of precision, recall, and F1 score.

[2] Zhang, Y., & Wallace, B. (2016). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820. The paper "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification" by Zhang and Wallace (2016) investigates the use of convolutional neural networks (CNNs) for sentence classification. The authors perform a sensitivity analysis to explore the effects of different hyperparameters on the performance of the CNN model, and provide a practical guide for practitioners on how to use CNNs effectively for sentence classification tasks. The authors use several benchmark datasets for sentence classification, including the Stanford Sentiment Treebank and the Movie Review dataset.

[3] Kumar, S., Aggarwal, A., & Singh, P. (2018). Offenseval: Identifying and categorizing offensive language in social media. arXiv preprint arXiv:1804.00058. The paper "OffensEval: Identifying and Categorizing Offensive Language in Social Media" by Kumar, Aggarwal, and Singh (2018) describes the Offensively shared task, which is a competition designed to encourage the development of machine learning models for identifying and categorizing offensive language in social media. The authors note that offensive language in social media can take many forms, including hate speech, cyberbullying, and harassment. They argue that automatic detection of such language is important for promoting a safe and respectful online environment.easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. METHODOLOGY

A. Data Collection

The data collection process involves obtaining images from various online platforms and social media channels, including a dataset, Memotion dataset available on Kaggle. The Memotion dataset contains approximately 6992 images (memes). These images contain textual content provides a diverse representation of offensive and non-offensive text samples.

	A	B	C	D	E	F	G	H	I
1		image_name	text_ocr	text_corrected	humour	sarcasm	offensive	motivational	overall_sentiment
2	0	image_1.jpg	LOOK THERE	LOOK THERE MY	hilarious	general	not_offen:	not_motivation	very_positive
3	1	image_2.jpeg	The best of #	The best of #10 Y	not_funny	general	not_offen:	motivational	very_positive
4	2	image_3.JPG	Sam Thorne (	Sam Thorne @Str	very_funn	not_sarca:	not_offen:	not_motivation	positive
5	3	image_4.png	10 Year Chall	10 Year Challeng	very_funn	twisted_m	very_offer	motivational	positive
6	4	image_5.png	10 YEAR CHA	10 YEAR CHALLE	hilarious	very_twist	very_offer	not_motivation	neutral
7	5	image_6.jpg	1998: "Don't	1998: "Don't get	hilarious	general	slight	motivational	negative
8	6	image_7.png	10 years chal	10 years challeng	not_funny	not_sarca:	not_offen:	not_motivation	negative
9	7	image_8.jpg	10 Year Chall	10 Year Challeng	very_funn	twisted_m	not_offen:	not_motivation	neutral
10	8	image_9.jpg	Fornite died i	Fornite died in 10	funny	not_sarca:	slight	motivational	positive
11	9	image_10.png	FACEBOOK '1	FACEBOOK '10 YE	funny	general	slight	motivational	positive
12	10	image_11.jpg	PROBABLY TI	PROBABLY THE F	funny	general	very_offer	motivational	negative
13	11	image_12.jpg	State Dining I	State Dining Roo	not_funny	very_twist	very_offer	not_motivation	very_positive
14	12	image_13.png	I did the Face	I did the Faceboo	very_funn	general	not_offen:	not_motivation	positive
15	13	image_14.png	IFIDOWNLOA	IFIDOWNLOADA	funny	general	not_offen:	not_motivation	positive
16	14	image_15.jpg	Anti-vaxx kid	Anti-vaxx kids wh	not_funny	not_sarca:	not_offen:	not_motivation	very_negative

Fig. 3 Labelled Data

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B. Data Preprocessing

The pre-processing steps are crucial to ensure that the data fed into the model is of high quality and consistent, improving its performance during training. Among these steps, image resizing and normalization play a key role in standardizing input sizes and promoting efficient model training. The primary goal is to maintain consistency of data input and facilitate optimal model performance. Resize requires resizing images to a specified size, ensuring consistency across the dataset.

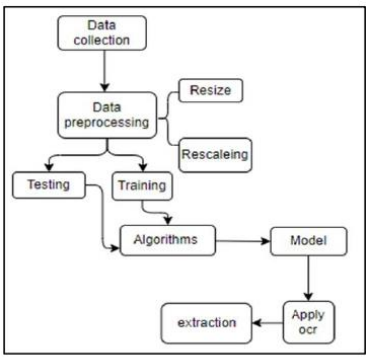

Fig. 4 Work-Flow Diagram

This step is crucial because models often require inputs of the same size. Normalizing images involves scaling the pixel values to a certain range, usually between 0 and 1. This process helps avoid problems with images having different brightness or contrast levels, which can otherwise affect model learning. Another useful technique is to use ImageDataGenerator, which makes it easy to add data. This process involves creating new training samples by applying transformations such as rotation, translation, zoom or translation to existing images. Data Augmentation is useful for increasing the variety and quantity of the dataset, which can lead to a more robust and generalized model. In general, by using data resizing, normalization, and augmentation techniques, preprocessing ensures that the input data is consistent.

C. Algorithm and Model

The suggested methodology tackles the challenge of identifying vulgarity in text contained within images. It starts by employing a pre-trained learning model, like MobileNet, to extract features from photos. Subsequently, it employs optical character recognition (OCR) technology to extract text from the image. This methodological approach offers fresh and practical approaches to online safety and content regulation by fusing machine learning with optical character recognition. The Adam optimizer is computationally more efficient, requires slight memory, is invariant to diagonal resizing of gradients, and it is well suited for problems with a lot of data/parameters. Now, Convolutional Neural Network (CNN) models are built to detect offensive content.

Fig.5 Tesseract OCR

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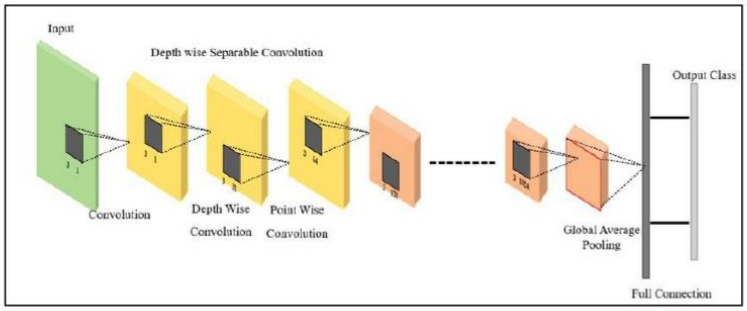

Fig. 6 MobileNet Architecture

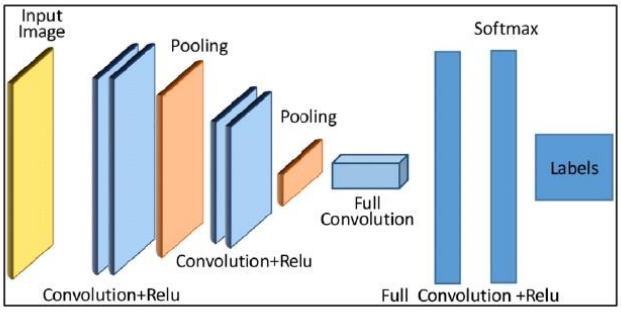

Fig. 7 CNN Architecture

IV. IMPLEMENTATION

The actual use of a learning model to recognize text in photos and determine whether or not it is offensive is also covered in length in this section. To extract text from photos, the method makes use of Tesseract and optical character recognition (OCR) in conjunction with TensorFlow and Keras within the MobileNet architecture. The major objective is to create a reliable system that can identify inappropriate text in photos automatically, making the internet a safer place. The photos in the dataset were taken from the local system directory. Every image has written content, along with annotations stating whether or not the text is inappropriate. To get the data ready for training, preprocessing procedures like scaling and normalization are used. The data was divided into five classes in the classification section: "Negative", "Neutral", "Positive", "Very Negative" and "Very Positive.

The MobileNet architecture, a deep convolutional neural network tailored for embedded and mobile applications, serves as the foundation for the model architecture. Additional layers for feature extraction and classification are included in the model, such as batch normalization, dropout layers, dense layers, and 2D global mean pooling. To specifically tailor the MobileNet model for the purpose of finding problematic text in photos, several layers are added to the main model. The Adam optimizer and a categorical cross-entropy function were used to train the model. Training parameters, such as batch size and number of epochs, are optimized for model performance and the training dataset is split into training and validation subsets. During training, methods like dropout regularization are employed to avoid overfitting. Using labeled data, the model finds patterns and links between image attributes and related qualities (like profanity detection) in this step. The technology allows the user to communicate with the trained model once it has been trained. the system offers functionality for users to interact with the trained model. Users can upload images for prediction, allowing the system to analyze and classify the textual content within the images accurately.

Furthermore, users can view the predictions generated by the system, gaining insights into the model's performance and the presence of abusive language in the uploaded images. It underwent rigorous testing to ensure reliability and effectiveness in detecting abusive content within images.

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Fig.8 Output of Trained Model

V. RESULTS AND DISCUSSIONS

In this section, we present the results obtained from our experiments and discuss their implications.

D. Offensive Text Detection

Our CNN-based approach to meme sentiment analysis has achieved significant success, showing high accuracy in classifying memes into different sentiment categories. With a dataset of 6992 images, by integrating MobileNet architecture and Tesseract's OCR, our system successfully detected offensive text from images. Our model reliably identified inappropriate text with an accuracy of 96%, helping content policing.

E. User Interaction and Transparency

Our system allows users to interact with the trained model, upload images for prediction and view model classifications. This transparency increases user trust and provides stakeholders with insight into the prevalence of offensive language in uploaded images. By offering users the opportunity to participate in the model, our system promotes accountability and encourages responsible sharing of content.

Fig.9 Home Page

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Fig. 10 Registration Page

Fig. 11 Login Page

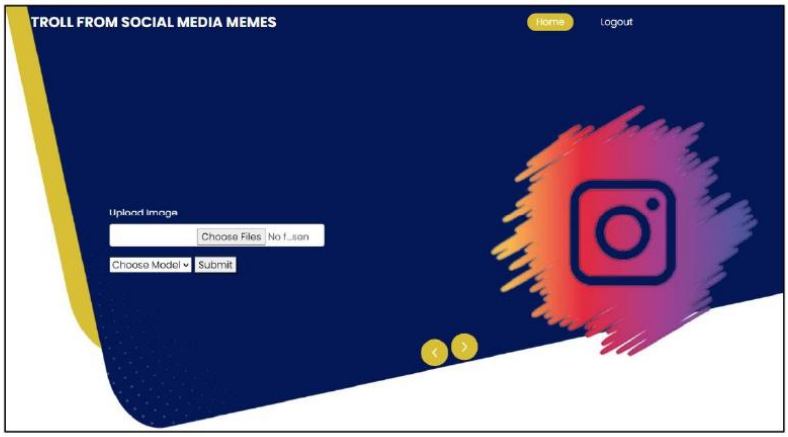

Fig.12 Image Upload Page

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Fig. 13 Result Page

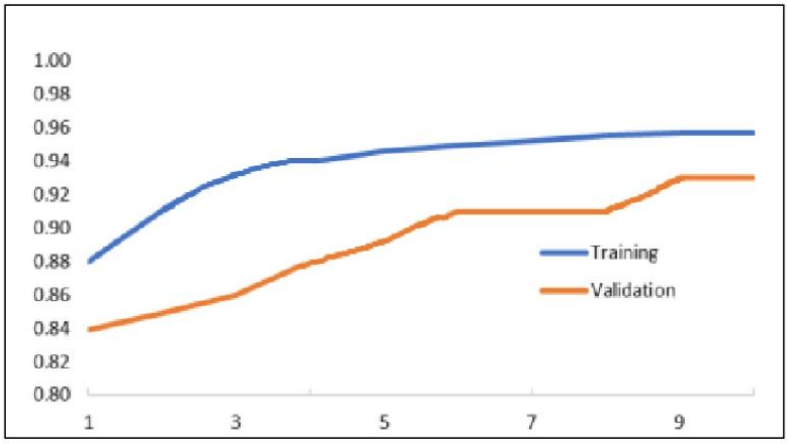

Fig.14 Model Accuracy Levels

F. Comprehensive Solution

We conducted a series of experiments to evaluate the performance of our proposed method for meme sentiment analysis and compare it with existing approaches. We conducted experiments on a dataset consisting of images extracted from memes, annotated with sentiment labels (positive, neutral, negative, very positive, very negative). The dataset was pre-processed to ensure uniformity in size and quality. The experiments were performed on a machine with Hard Disk 160GB, RAM 8GB using Python programming language and TensorFlow/Keras deep learning framework. We evaluated the performance of our model using standard metrics, including, accuracy. These metrics provide insights into the effectiveness of our method in accurately classifying meme sentiment. The results indicate that our proposed CNN-based approach effectively addresses the task of offensive text detection. The high accuracy and performance metrics demonstrate the robustness and effectiveness of our model in classifying memes into various sentiment categories.

Our findings have important implications for understanding sentiment dynamics in social media platforms. The improved performance achieved by our model can facilitate better sentiment analysis in content moderation.

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VI. CONCLUSION

In summary, the developed system provides a robust and scalable solution to detect offensive content in images using advanced machine learning techniques and capabilities for optical character recognition (OCR) with a model accuracy of 96%. By bringing these technologies together, the system enhances content moderation efforts..

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