Image Sentiment Analysis

Report for Project (CS794)

B. Tech in Computer Science & Engineering

B. P. Poddar Institute of Management & Technology

under

Maulana Abul Kalam Azad University of Technology

Under the supervision of

Dr. Bikromaditya Mondal
and
Mr. Suvadeep Bhattacharjee

Submitted by

Name:	Ankur Karmakar	Name:	Amit Kumar Agarwal
Roll No.:	11500216054	Roll No.:	11500116127
Regn. No.:	161150110134	Regn. No.:	161150110013
Name:	Modhura Das	Name:	Mampi Das
Roll No.:	11500116083	Roll No:	11500117015
Regn. No.:	161150110057	Regn. No.:	171150120009

Academic Year: 2019 - 2020

Department of Computer Science & Engineering
B. P .Poddar Institute of Management & Technology
137, V.I.P Road. Poddar Vihar, Kolkata – 700 052.

Department of Computer Science & Engineering
B.P.Poddar Institute of Management & Technology 137, V.I.P Road, Poddar Vihar. Kolkata – 700052

CERTIFICATE

This is to certify that the project work entitled "Image Sentiment Analysis**" submitted by Group No 11, comprising of (Amit Kumar Agarwal, Ankur Karmakar, Modhura Das, Mampi Das), has been prepared according to the regulation of the degree B. Tech in Computer Science & Engineering of Maulana Abul Kalam Azad University of Technology, West Bengal. The candidate(s) have partially fulfilled the requirements for the submission of the project work.**

(Signature of HOD)

Dept. of Computer Science & Engg.

(Signature of the Supervisor)

Dept. of Computer Science & Engg.

(Signature of External Examiner)

ACKNOWLEDGEMENT

It is a great pleasure for us to express our earnest and great appreciation to (*Dr. Bikromadittya Mondal and Mr. Suvadeep Bhattacharjee*), our project guide. We are very much grateful to them for their kind guidance, encouragement, valuable suggestions, innovative ideas, and supervision throughout this project work, without which the completion of the project work would have been a difficult one.

We would like to express our thanks to the Head of the Department, *Prof. Ananya Kanjilal* for her active support.

We also express our sincere thanks to all the teachers of the department for their precious help, encouragement, kind cooperation and suggestions throughout the development of the project work.

We would like to express our gratitude to the library staff and laboratory staff for providing us with a congenial working environment.

-- --
(Amit Kumar Agarwal) (Ankur Karmakar)

-- --
(Modhura Das) (Mampi Das)

(Full Signature of the Student(s))

Dept. of Computer Science & Engg.

B.P.Poddar Institute of Management & Technology

Table of Content

- Departmental Mission , Vision, PEO, PO, PSO
- Mapping with PO and PSO
- Justification of Mapping
- Abstract
- Activity Chart
- Introduction
  - What Is Sentiment Analysis
  - Applications Of Sentiment Analysis
  - Challenges For Sentiment
    - *Implicit Sentiment and Sarcasm*
    - *World Knowledge*
    - *Negation Handling*
    - *Diversity And Informality*
- Literature Review
- Gaps In Existing Work
- Theory
- Proposed System / Software
  - Advantages of Using VADER
- Feasibility Study
- Algorithm / Code
  - Code for Sentiment Analysis on Text Extracted From Image Using OCR and VADER Tool
  - Code for Sentiment Analysis on Faces
    - *Code for Sentiment Analysis on Faces Present in Image*
    - *Code for Sentiment Analysis on Faces Present in Live Video*
- Results & Discussions
- Future Plan
- References

1.1 DEPARTMENTAL MISSION

Enrich students with sound knowledge in fundamentals and cutting edge technologies of Computer Science and Engineering to excel globally in challenging roles in industries and academics.

Emphasize quality teaching, learning and research to encourage creative thoughts through application of professional knowledge and skill.

Inspire leadership and entrepreneurship skills in evolving areas of Computer Science and Engineering with social and environmental awareness.

Instill moral and ethical values to attain the highest level of accomplishment and personal growth.

1.2 DEPARTMENTAL VISION

Developing competent professionals in Computer Science and Engineering, who can adapt to constantly evolving technologies for addressing industrial and social needs through continuous learning.

1.3 PROGRAM EDUCATIONAL OBJECTIVES (PEOs)

Graduates of Computer Science and Engineering program will have good knowledge in the core concepts of systems, software and tools for analysing problems and designing solutions addressing the dynamic requirements of the industry and society, while employed in industries or work as entrepreneurs.

Graduates of Computer Science and Engineering program will opt for higher education and research in emerging fields of Computer Science & Engineering towards building a sustainable world.

Graduates of Computer Science and Engineering will have leadership skills, communication skills, ethical and moral values, team spirit and professionalism.

1.4 PROGRAM OUTCOMES (POs)

PO1: Engineering Knowledge: Apply knowledge of Mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design/Development of Solutions: Design solutions for complex engineering problems and design system components or processes that meet specified needs with appropriate consideration for public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct Investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: Engineer and Society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and Sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and Team Work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project Management and Finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long Learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

1.5 PROGRAM SPECIFIC OUTCOMES (PSO)

PSO1: Students will have proficiency in fundamental engineering and computing techniques and knowledge on contemporary topics like artificial intelligence, data science and distributed computing towards development of optimized algorithmic solutions.

PSO2: Students will have capabilities to participate in the development of software and embedded systems through synergized teams to cater to the dynamic needs of the industry and society.

2. PO & PSO MAPPING

Example given for your Reference:

PO1	**PO2**	**PO3**	**PO4**	**PO5**	**PO6**	**PO7**	**PO8**	**PO9**	**PO10**	**PO1**	**P012**	**PSO1**	**PSO2**
2	**3**	**3**	**2**	**3**	**3**	**3**	**2**	**3**	**1**	**2**	**2**	**2**	**2**

3. JUSTIFICATIONS OF MAPPING

- ➢ The project aims at solving a major challenge of analysing human emotion from various social media to take a variety of decisions by providing and developing a solution by understanding complex problem, thus justifying *PO2, PO3, PO4, PO6, PO7*.
- ➢ The project works on modern techniques such as Machine Learning and Artificial Intelligence, thus justifying *PO5*.
- ➢ Knowledge of statistics is required to apply ML and AI theorems, thus justifying *PO1*.
- ➢ The project can achieve its objective only when each and every member works as an individual completing his/her assigned work and also by acting like a team, consulting each other, thus justifying *PO9, PO10, PO11*.
- ➢ The project can be extended and modified accordingly with requirements and time, and also the completion of this project will contribute to the team members a life-long experience and learning, thus justifying *PO12*.

4. ABSTRACT

Large numbers of users share their opinions on Social networking sites, making it a valuable platform for tracking and analyzing public sentiment. Such tracking and analysis can provide critical information for decision making in various domains. So, it has attracted attention in both academia and industry. Presently, the use of public sentiment analysis has spread to services and making applications and developments came into existence in this area and now its main target is to make computer able to identify and create emotions like human beings. It is true that a picture is worth a thousand words. The use of images to express views, opinions, feelings, emotions and sentiments has increased tremendously on social platforms like Flickr, Instagram, Twitter, Tumblr, etc. The analysis of sentiments in user generated images is of increasing importance for developing several applications. A lot of research work has been done for sentiment analysis of textual data; there has been very limited work that focuses on analyzing sentiment of image data. In this paper, we are going to propose about development of an Image Sentiment Analysis Software using multi modal approach. We found that sentiment of an image can be more accurately determined by studying both faces of persons and text contained in the image.For getting sentiment of face in the image convolutional neural network (CNN) has been used to build a framework for designing real-time CNNs. Our models is validated by creating a real-time vision system which accomplishes the tasks of face detection, gender classification and emotion classification simultaneously in one blended step using our proposed CNN architecture. We are also going to introduce the very recent real-time enabled guided backpropagation visualization technique. Guided back-propagation uncovers the dynamics of the weight changes and evaluates the learned features.

Keywords: sentiment, sentiment analysis, human behavior analysis, sentiment analysis of textual data

5. ACTIVITY CHART

	Week 1 - Week 2	Week 3 - Week 5	Week 6 - Week 9	Week 10 - Week 17	Week 18 - Week 23	Week 24 - Week 25
Planning						
Requirements Gathering						
Designing						
Building						

Testing & Debugging						
Deployment						

6. INTRODUCTION

Being a major platform for communication and information exchange, internet provides a rich repository of people's verdict and sentiment about a vast spectrum of topics. Hence knowledge is embedded in multiple facets such as comments, tags, browsing and shared media. The analysis of such information either in the area of opinion mining, affective computing or sentiment analysis plays an important role in behaviour sciences, which aims to understand and predict human decision making and enables applications such as brand monitoring, stock market prediction, or political voting forecasts.

6.1 WHAT IS SENTIMENT ANALYSIS?

Sentiment Analysis is a process of Labelling Emotional States of data (which can be image, voice speech, video or text) and Information Extraction task that aims to automate the process of understanding attitude, emotions and opinions. It is a very challenging task. Researchers from natural language processing and information retrieval have developed different approaches to solve this problem, achieving promising or satisfying results. Generally speaking, sentiment analysis aims to determine the attitude of a person present in an image with respect to some text or the overall tonality of the image. In recent years, the exponential increase in the Internet usage and exchange of public opinion is the driving force behind Sentiment Analysis today. The Web is a huge repository of structured and unstructured data. The analysis of this data to extract latent public opinion and sentiment is a challenging task.
Liu et al. (2009) defines a sentiment or opinion as a quintuple-

> *"< o_j , f_{jk} , so_{ijkl} , h_i , t_l >, where o_j is a target object, f_{jk} is a feature of the object o_j , so_{ijkl} is the sentiment value of the opinion of the opinion holder h_i on feature f_{jk} of object o_j at time t_l , so_{ijkl} is +ve, -ve, or neutral, or a more granular rating, h_i is an opinion holder, t_l is the time when the opinion is expressed."*

6.2 APPLICATIONS OF SENTIMENT ANALYSIS

Word of mouth (WOM) is the process of conveying information from person to person and plays a major role in customer buying decisions. In commercial situations, WOM involves consumers sharing attitudes, opinions, or reactions about businesses, products, or services with other people. WOM communication functions based on social networking and trust. People rely on families, friends, and others in their social network. Research also indicates that people appear to trust seemingly disinterested opinions from people outside their immediate social network, such as online reviews. This is where Sentiment Analysis comes into play. Growing availability of opinion rich resources like online review sites, blogs, social networking sites have made this "decision-making process" easier for us. With the explosion of Web 2.0 platforms consumers have a soapbox of unprecedented reach and power by which they can share opinions. Major companies have realized these consumer voices affect shaping voices of other consumers.

Sentiment Analysis thus finds its use in Consumer Market for Product reviews, Marketing for knowing consumer attitudes and trends, Social Media for finding general opinion about recent hot topics in town, Movie to find whether a recently released movie is a hit.

Pang-Lee et al. (2002) broadly classifies the applications into the following categories.

A. Applications to Review-Related Websites
   Movie Reviews, Product Reviews etc.
B. Applications in Business and Government Intelligence
   Knowing Consumer attitudes and trends
C. Applications across Different Domains
   Knowing public opinions for political leaders or their notions about rules and regulations in place etc.

6.3 CHALLENGES FOR SENTIMENT ANALYSIS

Sentiment Analysis approaches aim to extract positive and negative sentiment bearing words from a text and image and classify these as positive, negative or else objective if it cannot find any sentiment bearing words and special facial expressions. In this respect, it can be thought of as a text categorization task. In text classification there are many classes corresponding to different topics whereas in Sentiment Analysis we have only 3 broad classes. Thus it seems Sentiment Analysis is easier than text classification which is not quite the case. The general challenges can be summarized as:

6.3.1 <u>Implicit Sentiment and Sarcasm</u>

A sentence may have an implicit sentiment even without the presence of any sentiment bearing words. Consider the following examples.

How can anyone sit through this movie?

One should question the stability of mind of the writer who wrote this book.

Both the above sentences do not explicitly carry any negative sentiment bearing words although both are negative sentences. Thus identifying semantics is more important in SA than *syntax detection*.

6.3.2 *World Knowledge*

Often world knowledge needs to be incorporated in the system for detecting sentiments. Consider the following examples:

He is a Frankenstein.

Just finished Doctor Zhivago for the first time and all I can say is Russia sucks.

The first sentence depicts a negative sentiment, whereas the second one depicts a positive sentiment. But one has to know about Frankenstein and Doctor Zhivago to find out the sentiment.

6.3.3 *Negation Handling*

Negation is a challenging task in SA. Negation can be expressed in subtle ways even without the explicit use of any negative words. A method often followed in handling negation explicitly in sentences like *"I do not like the movie"*, is to reverse the polarity of all the words appearing after the negation operator (like not). But this does not work for *"I do not like the acting but I like the direction"*. So we need to consider the scope of negation as well, which extends only till but here. So the thing that can be done is to change polarity of all words appearing after a negation word till another negation word appears. But still there can be problems. For example, in the sentence *"Not only did I like the acting, but also the direction"*, the polarity is not reversed after "not" due to the presence of "only". So this type of combinations of "not" with other words like "only" has to be kept in mind while designing the algorithm.

6.3.4 *Diversity And Informality*

In the context of social media, there are several additional unique challenges, i.e.

- There are huge amounts of data available.
- Messages on social networks are by nature informal and short.
- People use not only textual messages, but also images and videos to express themselves.

Since images are the easiest medium through which people nowadays express their emotions on social media so sentiment analysis of such large scale visual content can extract user sentiments towards particular events or topics. A good sketch is better than a long speech(*Napoleon Bonaparte*). People with different backgrounds can easily understand the main content of an image or video. Apart from the large amount of easily available visual content, today's computational infrastructure is also much cheaper and more powerful to make the analysis of computationally intensive visual content analysis feasible. In this era of big data, it has been shown that the integration of visual content can provide us more reliable or complementary online social signals.

7. LITERATURE REVIEW

It has been widely used area over the years and still it leaves a lot to be researched. Fried, Surdeanu, Kobourov, Hingle, Bell[1] investigated the predictive power behind the language of food on social media. They collected a corpus of over three million food-related posts from Twitter and demonstrate that many latent population characteristics can be directly predicted from this data: overweight rate, diabetes rate, political leaning, and home geographical location of authors. For all tasks, their language-based models significantly outperform the majority class baselines. Logunov, Panchenko[2] generated Twitter sentiment indices by analysing a stream of Twitter messages and categorising messages in terms of emoticons, pictorial representations of facial expressions in messages. Based on emoticons they generated daily indices. Then they explored the time-series properties of these indices by focusing on seasonal and cyclical patterns, persistence and conditional heteroscedasticity. Zhang, Parikh, Singh, Sundaresan[3] chosen a particular global ecommerce platform (eBay) and a particular global social media platform (Twitter). They quantified the characteristics of the two individual trends as well as the correlations between it. They provided evidence that about 5% of general eBay query streams show strong positive correlations with the corresponding Twitter mention streams, while the percentage jumps to around 25% for trending eBay query streams.Gonçalves, Araújo, Benevenuto, Cha[4] There are multiple methods for measuring sentiments, including lexical-based approaches and supervised machine learning methods. Despite the wide use and popularity of some methods, it is unclear which method is better for identifying the polarity (i.e., positive or negative) of a message as the current literature does not provide a method of comparison among existing methods. Such a comparison is crucial for understanding the potential limitations, advantages, and disadvantages of popular methods in analyzing the content of OSNs messages[6].

8. GAPS IN EXISTING WORK

1. Multi modal approach towards image sentiment analysis using text and face.
2. Analyzing emotions of multiple faces present in a photo frame, i.e. detection of multiple faces and analyzing the sentiment of each face.
3. Summing up the sentiments of multiple faces present in a photo frame to get the overall sentiment of all people present within the photo frame, i.e. generalization of overall sentiment of entire group consisting of multiple faces.
4. Analyzing the sentiment of the text present in an image
5. Sentiment analysis is done on images that are based on emotions, i.e. we try to find the facial expression of a person and based upon this we take a decision but we do not consider the external factors i.e. surroundings of a person in our decision making.

We argue that the careful implementation of modern CNN architectures, the use of the current regularization methods and the visualization of previously hidden features are necessary in order to reduce the gap between slow performances and real-time architectures.

9. THEORY

We have used multi-modal approach for sentiment analysis of an image. So there are two parts in analyzing sentiments -

- First one is getting sentiment from faces of person in the image. In this part, faces are detected and then convolutional neural networks (CNN) are used to find the sentiment and gender of faces present in the image. For this CNNs were trained using FER-2013 emotion dataset and gender classification was done using IMDB gender dataset. [5].
- Second one is getting sentiment from text present in images. For this Optical Character Recognition (OCR) technique was used with the help of pytesseract tool in Python for extracting the text from image. Then to analyse the sentiment of the extracted text VADER(Valence Aware Dictionary and Sentiment Reasoner) tool is applied on it that uses Natural Language Processing (NLP) to get the sentiment from the extracted text.

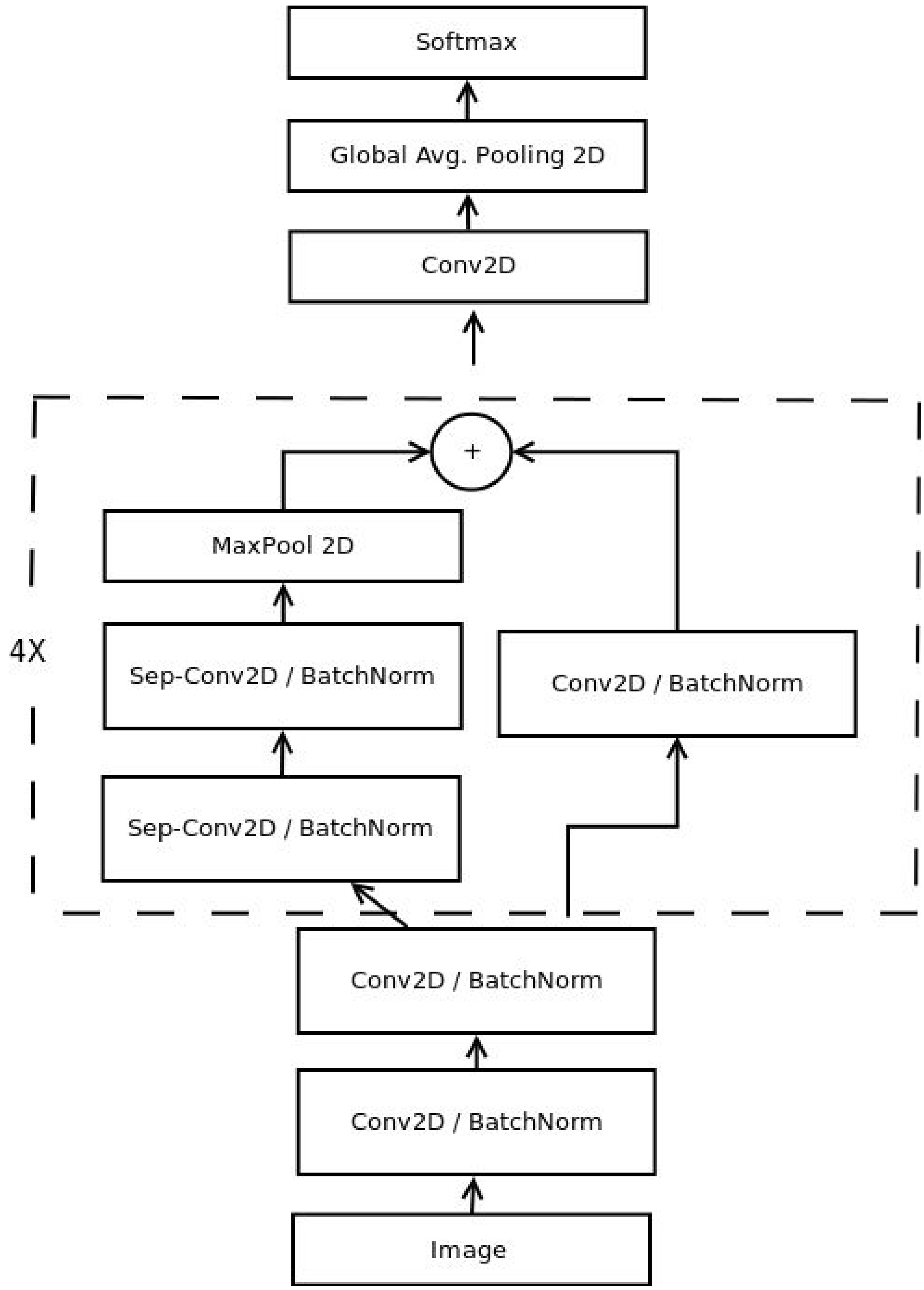
Fig. 1: Samples of the FER-2013 emotion dataset [1]

Fig 2: Samples of IMDB gender dataset [2]

After presenting the details of the training procedure setup we proceed to evaluate on standard benchmark sets. We report accuracy of 95.8% in the IMDB gender dataset, 66.2% in the FER-2013 emotion dataset and 96.35% in the face sentiment detection.

10. PROPOSED SYSTEM / SOFTWARE

Our proposed architecture for face sentiment analysis is a mini-Xception model [5] with standard fully-convolutional neural network composed of 9 convolution layers, ReLUs [3], Batch Normalization [4] and Global Average Pooling. This model contains approximately 600,000 parameters. It was trained on the IMDB gender dataset, which contains 460,723 RGB images where each image belongs to the class “woman” or “man”, and it achieved an accuracy of 96% in this dataset. We also validated this model in the FER-2013 emotion dataset. This dataset contains 35,887 grayscale images where each image belongs to one of the following classes {“angry”, “disgust”, “fear”, “happy”, “sad”, “surprise”, “neutral”}. The model achieved an accuracy of 66% in this dataset.

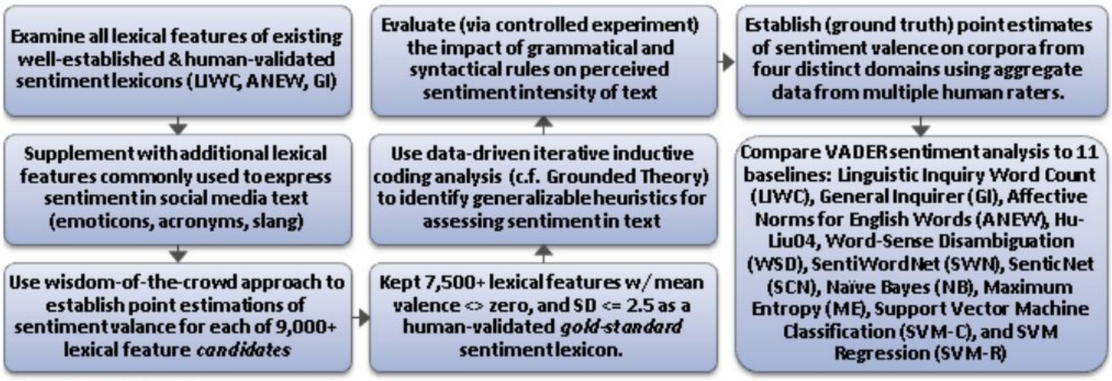


Model for real time classification of faces [5]

VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. VADER uses a combination of A sentiment lexicon is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative.

VADER has been found to be quite successful when dealing with social media texts, NY Times editorials, movie reviews, and product reviews. This is because VADER not only tells

about the Positivity and Negativity score but also tells us about how positive or negative a sentiment is.
It is fully open-sourced under the MIT License. The developers of VADER have used Amazon's Mechanical Turk to get most of their ratings, You can find complete details on their Github Page.



10.1 ADVANTAGES OF USING VADER

VADER has a lot of advantages over traditional methods of Sentiment Analysis, including:

- ➢ It works exceedingly well on social media type text, yet readily generalizes to multiple domains.
- ➢ It doesn't require any training data but is constructed from a generalizable, valence-based, human-curated gold standard sentiment lexicon.
- ➢ It is fast enough to be used online with streaming data.
- ➢ It does not severely suffer from a speed-performance tradeoff.

Let us check how VADER performs on a given review

sentiment_analyzer_scores("The phone is super cool.")

The phone is super cool----------------- {'neg': 0.0, 'neu': 0.326, 'pos': 0.674, 'compound': 0.7351}

Putting in a Tabular form:

Sentiment Metric	Score
Positive	0.674
Neutral	0.326
Negative	0.0
Compound	0.735

The Positive, Negative and Neutral scores represent the proportion of text that falls in these categories. This means our sentence was rated as 67% Positive, 33% Neutral and 0% Negative. Hence all these should add up to 1. The Compound score is a metric that calculates the sum of all the lexicon ratings which have been normalized between -1(most extreme negative) and +1 (most extreme positive). In the case above, lexicon ratings for and supercool are 2.9 and 1.3 respectively. The compound score turns out to be 0.75 , denoting a very high positive sentiment.

1. **positive sentiment**: `compound` score >= 0.05
2. **neutral sentiment**: (`compound` score > -0.05) and (`compound` score < 0.05)
3. **negative sentiment**: `compound` score <= -0.05

10.2 Python-tesseract

Python-tesseract is an optical character recognition (OCR) tool for python. That is, it will recognize and "read" the text embedded in images. Python-tesseract is a wrapper for google's Tesseract-OCR (http://code.google.com/p/tesseract-ocr/). It is also useful as a stand-alone invocation script to tesseract, as it can read all image types supported by the Python Imaging Library, including jpeg, png, gif, bmp, tiff, and others, whereas tesseract-ocr by default only supports tiff and bmp. Additionally, if used as a script, Python-tesseract will print the recognized text instead of writing it to a file. Support for confidence estimates and bounding box data is planned for future releases.

11. FEASIBILITY STUDY

11.1 Technical feasibility

In sentiment analysis of text present in an image first pytesseract tool is needed and for analyzing the sentiment of same VADER(Valence Aware Dictionary for Sentiment Reasoning) tool is needed. In sentiment analysis of faces present in an image, we have used python libraries like keras, openCV, numpy and utils.

11.2 Time feasibility

The entire project, i.e, solving all gaps, will require 2-3 months for completion.

11.3 Economic feasibility

The project does not require any additional hardware to perform (except its' performing platform), so there is no any added economic feasibility.

12. ALGORITHM / CODE

Required codes are described below.

12.1 Code for sentiment analysis on text extracted from image using OCR and VADER tool

```
# Import modules
from PIL import Image
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import pytesseract
# Include tesseract executable in your path
pytesseract.pytesseract.tesseract_cmd = r"C:\Program Files\Tesseract-OCR\tesseract.exe"
# Create an image object of PIL library
image = Image.open('H:\proj\ecc.jpg')
# pass image into pytesseract module
# pytesseract is trained in many languages
image_to_text = pytesseract.image_to_string(image, lang='eng')
# Print the text
print(image_to_text)

analyser = SentimentIntensityAnalyzer()
def sentiment_analyzer_scores(sentence):
    score = analyser.polarity_scores(sentence)
    print("{:-<40} {}".format(sentence, str(score)))

sentiment_analyzer_scores(image_to_text) #image_to_text contains extracted text
```

12.2 Code for sentiment analysis on faces

Sentiment can be analysed by studying faces present both in image and live video. Required codes are mentioned below:

12.2.1 Code for sentiment analysis on faces present in image

```
import sys
import cv2
from keras.models import load_model
import numpy as np

from utils.datasets import get_labels
from utils.inference import detect_faces
from utils.inference import draw_text
from utils.inference import draw_bounding_box
from utils.inference import apply_offsets
from utils.inference import load_detection_model
from utils.inference import load_image
```

```
from utils.preprocessor import preprocess_input

# parameters for loading data and images
image_path = sys.argv[1]
detection_model_path =
'../trained_models/detection_models/haarcascade_frontalface_default.xml'
emotion_model_path =
'../trained_models/emotion_models/fer2013_mini_XCEPTION.102-0.66.hdf5'
gender_model_path = '../trained_models/gender_models/simple_CNN.81-0.96.hdf5'
emotion_labels = get_labels('fer2013')
gender_labels = get_labels('imdb')
font = cv2.FONT_HERSHEY_SIMPLEX

# hyper-parameters for bounding boxes shape
gender_offsets = (30, 60)
gender_offsets = (10, 10)
emotion_offsets = (20, 40)
emotion_offsets = (0, 0)

# loading models
face_detection = load_detection_model(detection_model_path)
emotion_classifier = load_model(emotion_model_path, compile=False)
gender_classifier = load_model(gender_model_path, compile=False)

# getting input model shapes for inference
emotion_target_size = emotion_classifier.input_shape[1:3]
gender_target_size = gender_classifier.input_shape[1:3]

# loading images
rgb_image = load_image(image_path, grayscale=False)
gray_image = load_image(image_path, grayscale=True)
gray_image = np.squeeze(gray_image)
gray_image = gray_image.astype('uint8')

#extracting each face and storing in faces
faces = detect_faces(face_detection, gray_image)
for face_coordinates in faces:
    x1, x2, y1, y2 = apply_offsets(face_coordinates, gender_offsets)
    rgb_face = rgb_image[y1:y2, x1:x2]

    x1, x2, y1, y2 = apply_offsets(face_coordinates, emotion_offsets)
    gray_face = gray_image[y1:y2, x1:x2]

    try:
    rgb_face = cv2.resize(rgb_face, (gender_target_size))
    gray_face = cv2.resize(gray_face, (emotion_target_size))
    except:
    continue
```

```
        #gender classification
        rgb_face = preprocess_input(rgb_face, False)
        rgb_face = np.expand_dims(rgb_face, 0)
        gender_prediction = gender_classifier.predict(rgb_face)
        gender_label_arg = np.argmax(gender_prediction)
        gender_text = gender_labels[gender_label_arg]
        #sentiment analyzer
        gray_face = preprocess_input(gray_face, True)
        gray_face = np.expand_dims(gray_face, 0)
        gray_face = np.expand_dims(gray_face, -1)
        emotion_label_arg = np.argmax(emotion_classifier.predict(gray_face))
        emotion_text = emotion_labels[emotion_label_arg]

        if gender_text == gender_labels[0]:
        color = (0, 0, 255)
        else:
        color = (255, 0, 0)

        draw_bounding_box(face_coordinates, rgb_image, color)
        draw_text(face_coordinates, rgb_image, gender_text, color, 0, -20, 1, 2)
        draw_text(face_coordinates, rgb_image, emotion_text, color, 0, -50, 1, 2)

bgr_image = cv2.cvtColor(rgb_image, cv2.COLOR_RGB2BGR)
cv2.imwrite('../images/predicted_test_image.png', bgr_image)
```

12.2.2 Code for sentiment analysis on faces present in live video:

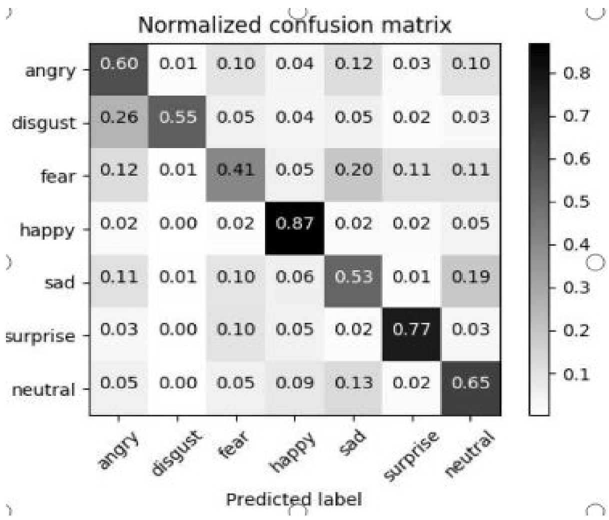
```
from statistics import mode

import cv2
from keras.models import load_model
import numpy as np

from utils.datasets import get_labels
from utils.inference import detect_faces
from utils.inference import draw_text
from utils.inference import draw_bounding_box
from utils.inference import apply_offsets
from utils.inference import load_detection_model
from utils.preprocessor import preprocess_input

# parameters for loading data and images
detection_model_path =
'../trained_models/detection_models/haarcascade_frontalface_default.xml'
emotion_model_path =
'../trained_models/emotion_models/fer2013_mini_XCEPTION.102-0.66.hdf5'
emotion_labels = get_labels('fer2013')
```

```
# hyper-parameters for bounding boxes shape
frame_window = 10
emotion_offsets = (20, 40)

# loading models
face_detection = load_detection_model(detection_model_path)
emotion_classifier = load_model(emotion_model_path, compile=False)

# getting input model shapes for inference
emotion_target_size = emotion_classifier.input_shape[1:3]

# starting lists for calculating modes
emotion_window = []

# starting video streaming
cv2.namedWindow('window_frame')
video_capture = cv2.VideoCapture(0)
while True:
    bgr_image = video_capture.read()[1]
    gray_image = cv2.cvtColor(bgr_image, cv2.COLOR_BGR2GRAY)
    rgb_image = cv2.cvtColor(bgr_image, cv2.COLOR_BGR2RGB)
    #extracting each face and storing in faces
    faces = detect_faces(face_detection, gray_image)

    for face_coordinates in faces:

        x1, x2, y1, y2 = apply_offsets(face_coordinates, emotion_offsets)
        gray_face = gray_image[y1:y2, x1:x2]
        try:
            gray_face = cv2.resize(gray_face, (emotion_target_size))
        except:
            continue

        gray_face = preprocess_input(gray_face, True)
        gray_face = np.expand_dims(gray_face, 0)
        gray_face = np.expand_dims(gray_face, -1)
        emotion_prediction = emotion_classifier.predict(gray_face)
        emotion_probability = np.max(emotion_prediction)
        emotion_label_arg = np.argmax(emotion_prediction)
        emotion_text = emotion_labels[emotion_label_arg]
        emotion_window.append(emotion_text)

        if len(emotion_window) > frame_window:
            emotion_window.pop(0)
        try:
            emotion_mode = mode(emotion_window)
        except:
```

```
            continue

        if emotion_text == 'angry':
            color = emotion_probability * np.asarray((255, 0, 0))
        elif emotion_text == 'sad':
            color = emotion_probability * np.asarray((0, 0, 255))
        elif emotion_text == 'happy':
            color = emotion_probability * np.asarray((255, 255, 0))
        elif emotion_text == 'surprise':
            color = emotion_probability * np.asarray((0, 255, 255))
        else:
            color = emotion_probability * np.asarray((0, 255, 0))

        color = color.astype(int)
        color = color.tolist()

        draw_bounding_box(face_coordinates, rgb_image, color)
        draw_text(face_coordinates, rgb_image, emotion_mode,
                  color, 0, -45, 1, 1)

    bgr_image = cv2.cvtColor(rgb_image, cv2.COLOR_RGB2BGR)
    cv2.imshow('window_frame', bgr_image)
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break
video_capture.release()
cv2.destroyAllWindows()
```

13. RESULTS & DISCUSSIONS

Results of sentiment analysis on faces can be observed in figure 3 and figure 4. Along with sentiment analysis we have also done gender classification.
The confusion matrix results of emotion classification is:



We can observe several common misclassifications such as predicting “sad” instead of “fear” and predicting “angry” instead of “disgust”.

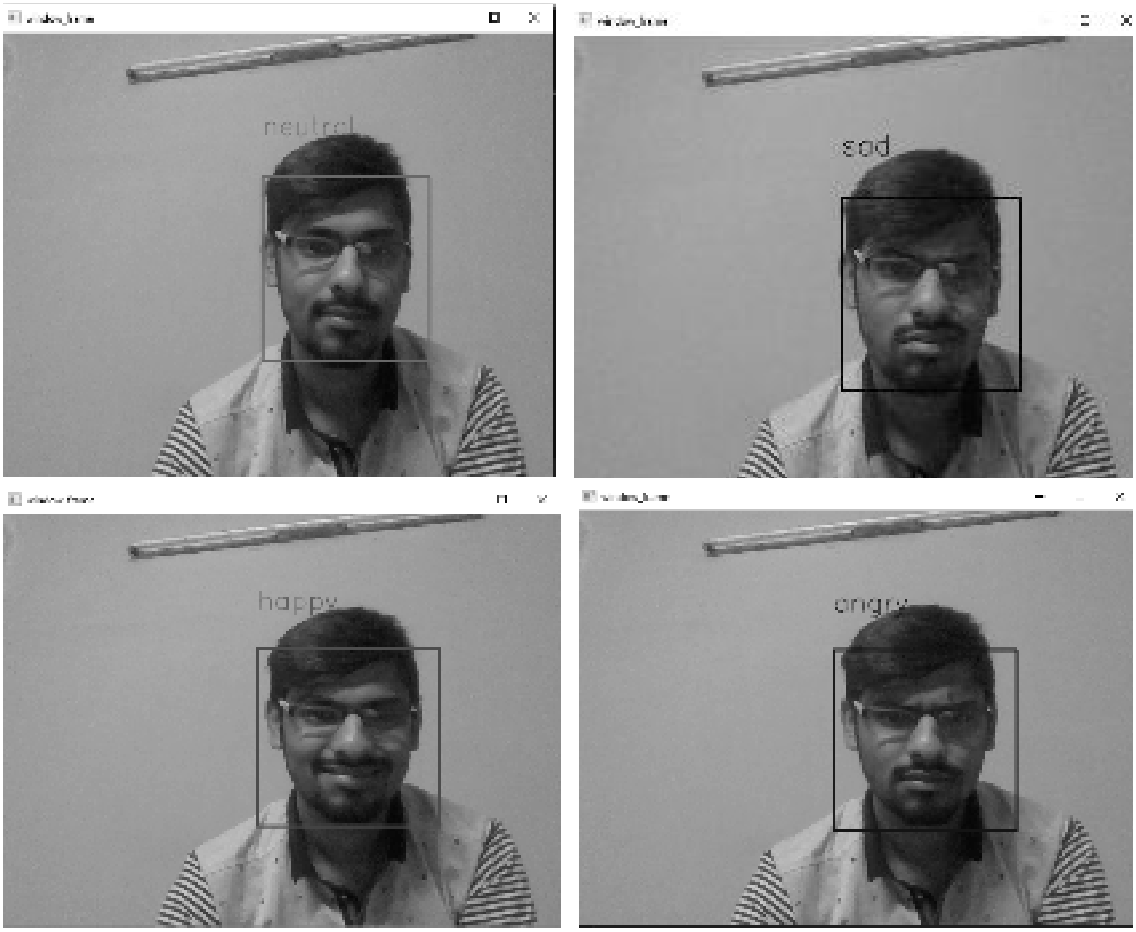


Figure 4. Sentiment Analysis of face present in live video

In figure 4, faces present in an image frame of live video stream are detected and then emotion is analysed. Here, 4 kinds of emotions are detected - neutral, sad, happy and angry.

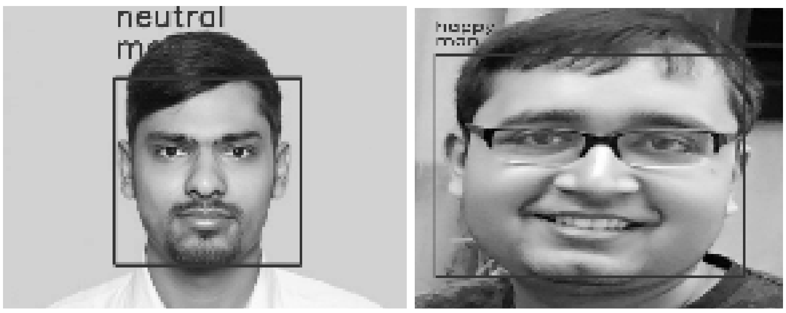


Figure 5. Sentiment analysis of faces present in an image

In figure 5, faces present in an image are detected and then emotion is analyzed along with the gender.

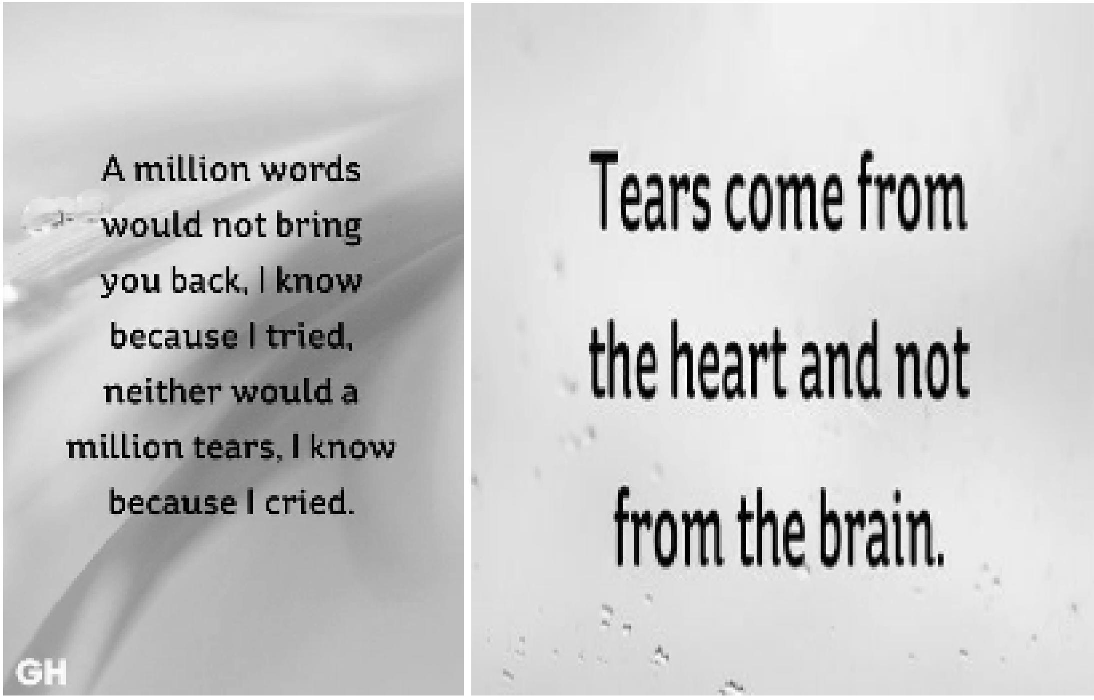


Figure 6. Samples of images containing texts for sentiment analysis

```
C:\Users\hp\Desktop\Project_Final\src>python text_image.py
A million words

~ would not bring

you back, | know

because | tried,

neither would a
million tears, | know

because | cried.
A million words

~ would not bring

you back, | know

because | tried,

neither would a
million tears, | know

because | cried. {'neg': 0.135, 'neu': 0.779, 'pos': 0.086, 'compound': -0.2344}

C:\Users\hp\Desktop\Project_Final\src>python text_image.py
Tears come from
the heart and not
from the brain.
Tears come from
the heart and not
from the brain. {'neg': 0.174, 'neu': 0.826, 'pos': 0.0, 'compound': -0.2263}
```

Figure 7. Result of sentiment analysis of text present in image

The compound value decides finally whether the sentiment is positive, negative or neutral. If the compound value is greater than or equal to 0.05 then it is positive sentiment, if the compound value is less than or equal to -0.05 then it is negative sentiment, otherwise it is neutral sentiment sentiment.

Figure 8. Sentiment analysis of image containing both text and face

14. FUTURE PLAN

Sentiment analysis is not all that smooth after all. There are several issues related to Sentiment analysis that could lead to the loss of popularity of the technique I.e. opinion spam, e result measure, lack of complete information etc. Despite all the challenges and potential problems that threatens Sentiment analysis, one cannot ignore the value that it adds to the industry. Because Sentiment analysis bases its results on factors that are so inherently humane, it is bound to become one of the major drivers of many business decisions in the future. Improved accuracy and consistency in text mining techniques can help overcome some current problems faced in Sentiment analysis. Looking ahead, what we can see is a true social democracy that will be created using Sentiment analysis, where we can harness the wisdom of the crowd rather than a select few “experts”. A democracy where every opinion counts and every sentiment affects decision making.

Machine learning models are biased in accordance to their training data. In our specific application we have empirically found that our trained CNNs for gender classification are biased towards western facial features and facial accessories. We hypothesize that this misclassifications occurs since our training dataset consist of mostly western: actors, writers and cinematographers as observed in Figure 2. Furthermore, as discussed previously, the use of glasses might affect the emotion classification by interfering with the features learned. However, the use of glasses can also interfere with the gender classification. This might be a result from the training data having most of the images of people wearing glasses assigned with the label “man”. We believe that uncovering such behaviours is of extreme importance when creating robust classifiers, and that the use of visualization techniques such as guided back-propagation will become invaluable when uncovering model biases.

15. REFERENCES

[1] Ian Goodfellow et al. Challenges in Representation Learning: A report on three machine learning contests, 2013.

[2] Rasmus Rothe, Radu Timofte, and Luc Van Gool. Deep expectation of real and apparent age from a single image without facial landmarks.

[3] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. Deep sparse rectifier neural networks. In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, pages 315–323, 2011.

[4] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International Conference on Machine Learning, pages 448–456, 2015.

[5] Octavio Arriaga, Paul G. Ploger, Matias Valdenegro: Real-time Convolutional Neural Networks for Emotion and Gender Classification

[6] Sentiment Analysis on Social Networking: A Literature Review by Prof. Durgesh M. Sharma (Department Of Computer Technology, M.I.E.T, Gondia, India) and Prof. Moiz M. Baig (Department of Computer Science and Engineering, J.D.C.O.E.M, Nagpur, India)