Neural Network-Based Cyber-Bullying and Cyber-Aggression Detection Using Twitter Text

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Research Article

Keywords: Cyberbullying, Cyberaggression, System Architecture, Sentiment detection

Posted Date: July 22nd, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1878604/v1

Abstract

Cyber-bullying and Cyber-aggression has led to lots of death of individuals, mental instability of victims, increase in frustration, anger, decrease in confidence, stress, fear of the unknown, tension, sleep disorder amongst others. The availability of internet which has brought about social networking; various social media platforms now exist providing space for varied expressions and opinions. Nevertheless, due to dynamic nature and easy access of the platform, the use spiteful and hateful words have promoted Cyber-bullying and Cyber-aggression. Thus, approximately half of young social media users experiences digital harassment such as Cyber-bullying and Cyber-aggression. In this research, a sentiment detection system is proposed using the text data. RNN is used for the text analysis and CNN for image analysis. The text data is generated from Twitter through Twitter API. The efficiency and performance of models were evaluated with RNN and CNN outperforming the other classification algorithms achieving accuracy of 0.951 and 0.911 also, F-Measure scores were 0.910 and 0.890 respectively.

Introduction

The availability of internet has brought about social networking; various social media platforms exist contributing in the world becoming a global village. They are provide space for expression and opinion where people seeking to build network with people all over the world, to either share their personal life affairs or their opinion on issues that concerns the world at large or their perception about anything. The era of one-way communication is gone; today's media is pervasively playing a big role of disseminating information for individual.

Human activity and behaviours in all spheres of life are influenced by others opinion which serves as a source of feedback system. One's attitude and perception of reality, as well as the decisions taken, are heavily influenced by how others perceive and weigh their words. Raw data gathered from posts, comments, impressions, emotions or emoji, are potential information on social media after being processed. (Abdur 2019;Shetty et al.2021). Social media platform as a two-sided sword has caused so many anti-social behaviours that are no longer a function of age but everyone is affected. The dynamic nature and easy access of the platform has promoted the spiteful and hateful use of it. The basis of social media as a constructive and positive platform has been overshadowed with unpleasant and abusive behaviours. Over half of young social media users experiences digital harassment such as cyber-bullying and cyber-aggression. This digital harassment can take any form; however, recurring and aggressive behaviour performed by a set of people or an individual and some actions that can later be considered as unpleasant, derogatory, injurious, or unwanted, which can be regarded has a usual form of cyber-bullying and cyber-aggression (Bhakar 2019;Kumar et al. 2021).

Sentiment Analysis (SA) is the utmost progressive research field in natural language processing that focuses on identifying the emotions of a writer behind the series of words and classifies public attitude, opinion from visuals, audios and texts (Pandey et al.,2019). It is a computational technique that can help study people's attitude, views and opinion over the web for different entities. Sentiment analysis uses social media as its important source of information because it continuously expands and breeds consistent and multifaceted information. It is a technique that falls under the Supervised Machine Learning Techniques, where subjective information is extracted, comprehended and distributed into categories. Across the social networking sites, the surge for user generated content as drastically increased. And among all, twitter is the social network platform that records huge volume of opinionated information (Soumyabrata et.al, 2018; Sherly et al. 2021).

Recognizing a person's true view from a piece of text, his/her speech, facial expressions, videos, or image might be challenging at times, however automatic sentiment recognition by a computer could help solved the problem.The society is beginning to believe that cyber-aggression and cyber-bullying is a no big deal or repeatedly annoying someone is a social media stunt because several digital harassments go unpunished. Embarrassment, depression, sleep disorder, isolation from other community members tends to be the lot of digital harassment victims with negative consequences such as, attempting suicide. Despite advancements in information security, such as cryptography and data protection techniques, cyber-attacks remain a significant problem to address.

About 87% of young people have been seen cyber-bullied on social media and causing both social, health and behavior problems on users. Most suicidal cases would have been curbed if robust sentiment analysis systems are in place, which is psychological in tune to read beyond users' tweets. On an average, 3.6 million tweets are tweeted on twitter every minute. So, the more volume of data poses a problem to data analysts to draw an opinion out of it. Intonation, facial expression, thought and opinion in text, video or image, can sometimes be very difficult to encode. Bottleneck in the process of extracting frames, audio, text obtained from videos, textual information and images can make analysis impossible or very tedious. Also, as a large collection of people's opinions on the internet keeps increasing, drawing conclusion from an unstructured data can be quite tasking. Social media users often express their views in different ways regardless of their spoken language and the way they all write, it is different whereby some can write using smileys, slogans or sarcasms.

From the literatures it is evident that methods used haven't been able to completely keep up with the dynamic nature of present social media platforms, it's majorly on textual information and the most generally used approach for detecting cyber-bullying and cyber-aggression behaviour is training and assessing classifiers on the static data.

The aim of this study is to implement a a users' tweet monitoring system for detecting cyber-bullying and cyber-aggression. It uses a recurrent neural network to look for word relationships and a convolutional neural network for opinion prediction in videos and images, spotting them with aggressive or bully views. The total number of tweets used locally for testing the system was 700 as at the time of this write up while awaiting API keys approval from Twitter.

Our contributions are summarized as follows:

• We propose to construct have capacity for analyzing images or videos for classification not only text as commonly available.

• We hybridized Convolutional Neural Network with LSTM-RNN for a better accuracy and optimal performance. The CNN enables images/videos to be digitally processed thereby giving the system to mine textual information from both videos and images, which may then be passed to the LSTM-RNN network, which is mainly built to handle textual tweets. The LSTM was added to the Recurrent Neural Network in order to solve the problem of texts with long time dependencies usually referred to as vanishing gradient.

Performance evaluation shows Deep Neural Network (DNN) outperformed the other classification algorithms. Finally, we summary and discuss our work in Conclusion section. The rest of the work includes literature review, methodology, implementation and conclusion.

Literature Review

According to Mohssen M.B, (2017) Artificial Intelligence is a branch of computer science concerned with the creation of intelligent machines that function and respond in the same way that humans do (AI). Artificial intelligence (AI) is the intelligence exhibited by machines or software.

The fundamental practice of machine learning is acquiring data, learning from it, and finally making a conclusion and predicts something about the world. This is In contrast with conventional programming, where an identified feature can be used to explicitly program an algorithm. Machine learning creates an algorithm with a narrative or a different blend of characteristics and weights than may be determined from the core notion using subsets of data. (Matthew, 2020). Fig.1 shows the differences between conventional programming and machine learning paradign. In conventional programming (A), a computer with a dataset and an algorithm exists. The algorithm instructs the computer on how to generate outputs ahead of the dataset. A computer with a dataset and connected outputs is used in machine learning (B). The computer learns and develops an algorithm to depict the relationship between the two.

The inspiration of having biological process of neural network a supervised machine learning method, dominating all kinds of applications and proving great advantage over conventional programming, as brought about Deep learning. A deep learning technique allows direct learning from the data for all aspects of the model. It starts with the lowest level attributes, which provide an accurate representation of the data. When the amount of training data is increased, deep learning becomes more useful. Because of the growing magnitude of data and breakthroughs in the field of big data, traditional machine learning algorithms have revealed their limitations in analyzing large datasets. In the purpose of analysis, deep learning algorithms have produced superior results. It has made a distinction between machine learning techniques and traditional algorithms by taking advantage of more human brain competence (Garg, 2018).

Sentiment Analysis

Sentiment analysis is a computational exploration that deals with recognizing and indulging opinions and sentiments expressed in text, video or image. Sentiment analysis has its roots as far back as 1980s. Their predecessors were programs that looked into "belief analysis." Wilks and Carbonell developed a computer system for assessing subjective comprehension. In the late 1990s, Hatzivassiloglou and McKeow looked at adjectives wit written text, which is studied in NLP. It is also a subject of web mining, information retrieval, and text data mining. (Ali, 2018).

Cyber-Bullying and Cyber-Aggression

Cyber-bullying and cyber-aggression are gradually becoming more bothersome experience affecting people across all demographics. More than half of young social media users worldwide have been exposed to such prolonged and/or coordinated digital harassment. Common bullying is referred to as face-to-face bullying, with intention to cause harm on victims repeatedly over time, with displaying inequality of power between the victim(s) and bullies or aggressor. Nevertheless, with the invention of cyber-bullying and cyber-aggression surfacing, abuse of individuals is no

Longer confined to the face-face setting, nor is it limited to the usual daily habit of human interaction; uniqueness that bind instances of common bullying. Indeed, but the use electronic devices and media to harass someone in nearly any location, and at any time, is a distinct feature of cyber-based mistreatment. However, Cyber-bullying is the use of social media platform to bully other users by sending daunting, intimidating or offensive messages. Victims can sometimes be faced with life-threatening or psychological consequences (Thirupathi, 2017). Cyber-bullying is described as measures that abuse information and communication technology to assault victims deliberately, repeatedly and through an inequality of power. Different types of cyber-bullying include furious (fiery exchange between individuals), nuisance (repetitive and aggressive bullying of a victim), defamation (disseminating derogatory and untrue information about a victim), and imposture (stealing victim's online identity and posing as a victim to communicate embarrassing information regarding the victim to others) (Chatzakou, 2019).

Theoretical Framework

The general strain theory deals with how a negative relationship affects an individual and their future possible development towards crime and bullying. Although there are various theories that look at an individual's social relationships and how they encourage crime and bullying, General strain theory also looks at the social relationships of an individual, but the theory focuses more on the negative aspect of relationships. According to

tweeter statistics, 2019 was recorded to have the highest number of cyber bullying. We can conclude from the theory that this level of cyber bullying is caused by the effect of negative relationship tweeter users have had in the past.

Related Works

Despoina et al., (2017) Built a model for detecting Cyber-bullying and Cyber-aggression in social media using the Machine Learning Algorithm. Deep neural networks, as well as probabilistic, tree- based, and ensemble classifiers like Naive Bayes and I in terms of performance and training time. The gap of the study is that system did not provide detect abusive behaviour in real time.

Mangaonkar, (2017) Provided a collaborative approach for detecting cyber-bullying in tweets using different distributed collaboration patterns. With the aid of Support Vector Machine, Naive, and Maximum Entropy (Logistics) machine learning algorithms, the model was trained to create models that were used for the classification of cyber-bullying tweets. Various experiments carried out indicate that the collaborative approach performs better than the stand-alone approach. There was an overhead that caused the classification time to increase as number of nodes in the network increased.

Kshitiz et al., (2018) Used NLP and Machine Learning in detecting Cyber-bullying and Aggression. Random Forest, strive to determine the most optimal in terms of performance and training time. The gap of the study is that system did not provide detect abusive behaviour in real time.

Rolfy et al., (2018) Developed an automatic Cyber-bullying detection system in Spanish-language social network. Researchers recommended that for improved performance, adding words from other nations should be considered to the word exchange.

Fadelli, (2019) Developed a new approach to detect cyber-bullying on Twitter using deep learning called optimized Twitter cyber-bullying detection (OCDD). Where hard task features are extracted from tweets and feed them to a classifier, and tweets are represented as a set of word vectors which captures the semantic of words and CNN which classifies tweets in a more intelligent way than traditional classification algorithms. The gap of this study is that cyber-bully was not evaluated within detection contexts.

Ravindran et al., (2020) Built a model to detect suspicious posts on online forums using Machine Learning in Text mining. No source of data stated and model was not adequately trained to handle a range of sentiments.

Arathi et al., (2021) Built a model to detect the presence of Cyber-bullying using Machine Learning approach. Enhancing the detection of Cyber-bullying by combining texts with videos and images was recommended by the researcher.

Banoth et al., (2021) Proposed the Multinominal Naive Bayes Classifier for detecting Cyber-bullying Tweets. The gap of this work, is that, the researcher didn't do analysis on the topic modeling.

Chong et al., (2021) Developed a model to test the performance of machine learning approaches in Cyber-bullying detection from social media using sentiments. The researchers suggested that

other models or algorithms, aside from Nave Bayes, Support Vector Machine (SVM), and k- Nearest Neighbor (k-NN), can be used in investigated in order to obtain more accurate and efficient findings.

Muhammad et al., (2021) Worked on Cyber-bullying Detection by Sentiment Analysis of Tweets' Contents Written in Arabic in Saudi Arabia Society. Hybrid (i.e., both Machine Learning & Lexicon-Based) was used for the methodology. The researchers suggested that for considerably better outcomes, neural networks or deep learning algorithms could be used.

Methodology

The System Architecture

The graphical representation of the logical organization of a system's sub-components is normally referred to as the system architecture. Most sentiment analysis systems do their categorizations or classifications based on textual information only; and such classification is always into positive, negative or neutral. In other words, they normally do not have capacity for analyzing images or videos for classification, hence the need for a better system, which this research work has attempted to design. This work hybridized Convolutional Neural Network with LSTM-RNN for a better accuracy and optimal performance. The CNN enables images/videos to be digitally processed thereby giving the system to mine textual information from both videos and images, which may then be passed to the LSTM-RNN network, which is mainly built to handle textual tweets. The LSTM was added to the Recurrent Neural Network in order to solve the problem of texts with long time dependencies usually referred to as vanishing gradient.

Fig.2 shows the architectural design of the Cyber-Aggression and Cyber-Bullying detection system developed in this project. The architecture is made up of two main layers namely; The Output Layer also known as the user interface layer and the Hidden Layer that consists of several other sub-components. These layers with their embedded components are fully explained as follows:

Data collection strategies are created to retrieve chronological tweets from Twitter endpoints. This research work makes use of Twitter Standard Search which is a platform for public information streaming. Application Programming Interface, a user interface that allows you to retrieve information in chronological sequence from twitter public domain. This API enables the system to download recent tweets that serve as input to the analyzer in real time.

Image Dataset

The image dataset is a collection of millions of well labeled and trained image data that serves as resources for the CNN component of the system. The main source of image data used in this project work is Google's Open Images, which is an image datas million images that have been annotated with image-level labels and object bounding boxes. The reason for using this dataset was because, as the time of this write up, it is one of the largest image datasets freely available for download from Google website with no barriers, approximately 80% of the data set was used to train while the remaining 20% was for testing purposes. It is important to state that video inputs are chunked into image-like frames and treated as images too.

Text Dataset

Like the Image Dataset, the text dataset is a collection of tweets from twitter domain that have been trained and well labeled. Used for this project is sentiment140 dataset containing about 1.6 million well annotated tweets extracted from twitter website using twitter API.

Input Identifier

The input identifier component is one that gets information from twitter Application Programming Interface (twitter API) as they are being downloaded from twitter domain in real time. The main purpose of this component is that it pre-processes the input and sends the pre-processed data to the appropriate component. It has capacity to separate image/video from text, thereby sending image/video to the Convolutional Neural Net Time Memory Recurrent Neural Network for further processing.

CNN

In this research work, the introduction of Convolutional Neural Network is mainly to generate the textual representation of any tweeted image/video and passes

counterpart for proper analysis and classification. Considering the CNN component in the architecture in Fig, 2 from left to right, the input is an actual image that is scanned for features, and the light rectangle is the filter that passes over it. Stacked on top of one another in a stack is the activation map one for each used filter, which condensed via down sampling. The larger rectangle represents a patch that will be down sampled. By passing the filters over the first down sampled stack, a new collection of activation maps is formed while the 2nd down sampling condenses the 2nd group of activation maps and finally, a completely linked layer that assigns a label to each node's output.

CNN applies a filter to the connection by the addition of two new kinds of layers namely; pooling and convolutional layers. The convolutional layer is the first layer in the architecture, which at first, breaks down an input image into a series of 3 * 3-pixel tiles square that overlap each of this will be run on a neural network with the weights left intact, resulting in the collection of tiles being transformed into an array. The output values will then be collected and placed in an array that numerically represents the content of each section content in the image, with color, width, and height channels on the axes thus leaving every tile with a 3*3*3 a three-dimensional representation. A fourth dimension for time will be added in case of videos.

LSTM-RNN

Regular Recurrent Neural Network hidden layers are unable to successfully store information about very long sentences, hence the need to build hidden layers with gate-operated memory unit capable of retaining the encoding done in the state for a long time. This type of RNN is called Long Short-Time Memory Recurrent Neural Network (LSTM-RNN) capable of solving the problem of lack of long-range dependencies in the system. In this research work, LSTM-RNN is purposely built to enable easy mining of opinion from textual information derived from real-time tweets with considerations for texts with both short- and long-term dependencies usually referred to as vanishing gradient problem. The network is specially designed to accommodate phrases and sentences coming from real-time tweet, get them encoded and produces an output based on its last time step, which on purpose is then passed to a softmax activation function.

Softmax

The softmax function, also known as softargmax or normalized exponential function, is an activation function, which is a generalization of the logistic function to multiple dimensions. It is used as the last activation function of the LSTM-RNN to normalize the output of the network to a probabilistic distribution over predicted output class.

Matcher

The matcher is an output generating component by taking as an input the result of the network last activation function. It uses the result to match with the ones stored in the dataset. When a match is found, then the matcher fetches and displays the corresponding label of the softmax value. For example, consider the following dataset structure:

1. Sentence: “I will show you the stuff I am made of” | Label: “Bully”
2. Sentence: “I will show you the place” | Label: “Neutral”
3. Sentence: “I will show but not now!” | Label: “Aggressive”
4. Sentence: “I will not show you because we are not mates” | Label:” Aggressive”

Considering the above, let say an input tweet reads: “I won’t because we are not mates”, then the softmax will like produce a value close to 4 and matcher will c this case will be sentence 4 and displays the Label (i.e., Aggressive). It is worthy of note that generalization can be done and the overall output can be represented in graphical form according to specification.

System Implementation

The system designed in this paper was implemented as a stand-alone application that runs on desktop computer systems. The application has different functional modules and user interfaces.

Development Tool

The system is implemented using python programming language. Python coding was done in python Integrated Development Environment called PyCharm. Tweepy, a Python library for accessing the Twitter API was also used. The Twitter Application Programming Interface (API) enables our python code to access and use twitter data in real-time. Hypertext Mark-Up Language (HTML) and Cascading Style Sheet (CSS) were used for the interface design while JavaScript was used to pass data to/from Python and HTML elements through the use of electron. Electron is a python plugin that enables python code to run or execute on a standard web browser.

Interface Design

The graphical user interfaces (GUIs) were carefully designed to be simple and user friendly. The sentiment analyzer for detecting cyberbullying and aggression developed in this work has five main pages namely; User Login page, New User Registration page, Application Welcome page, Search page, Output Display Page.

The user login page provides some levels of security to the developed belief rule base expert system platform. The user registration page that enables new users to submit their information such as full name, username and password, etc. to the system’s database. The information, especially the username and password, are used by the users during login. The system checks whether the supplied username and password match the one registered for the underlined user. If the login details match the one in the database, then the user is logged in successfully and taken to the Keyword Search Page, otherwise the user is denied access into the system.

The keyword search page shown in Fig. 4 as presented below is a simple but very important page, among other pages, which enables the user to actually streamline his search parameters. For instance, this page can be used to check whether a child has been bullied or not by simply entering the child’s twitter name or id into the box in front of the ENTER KEYWORD label and then click on the DISPLAY ANALYSIS button.

The output display page shown in Fig.5 enables the user to visualize the result of the system’s analysis of his keyword. Depending on the keyword, the sentiment analyzer has the capability of displaying the result in a number of graphical formats as may be desired by the user including Histogram, Bar Chart,

Pie Chart, Line graph, Scattered Line Graph, etc. For easy understanding by the user, Pie chart is used to display the result in this project because it easily categorizes the result into two on the chart namely; Cyberbullying/Aggression and Others.

The Cyberbullying/Aggression category on the chart indicates the level or percentage of bullying or aggressive words contained in the tweets being deployed while the other category indicates those tweets void of such words that can be interpreted as bullying or aggression.

The total number of tweets used locally for testing the system was 700 as at the time of this write up while awaiting API keys approval from Twitter. From the above pie chart, the analysis showed that, out of the 700 tweets deployed to the system, only 219 tweets can be interpreted to be inform of bullying or aggression (Negative) while the remaining 481 tweets can be interpreted as neither bullying nor aggression (i.e., Positive and Neutral).

Results And Discussion

For the purpose of performance measurement, already pre-processed dataset from sentiment140 was used to train classification models such as Logistic Regression, Naive Bayes, K-Nearest Neighbors, Random Forest, Stochastic Gradient Descent (SGD) and Support Vector Machines in addition to the DNN (CNN and RNN) developed in this work. It was so apparent that Deep Neural Network (DNN) outperformed the other classification algorithms as presented in the following table.

Table 1 Input Samples

SN	MODEL	ACCURACY	F-MEASURE
1	Logistic Regression	0.671	0.637
2	Stochastic Gradient Descent	0.655	0.601
3	Bernoulli Naïve Bayes	0.64	0.605
4	Random Forest	0.558	0.512
5	K Nearest Neighbour	0.543	0.476
6	Linear Support Vector Machine	0.669	0.648
7	Recurrent Neural Network	0.951	0.910
8	Convolutional Neural Network	0.911	0.890

The model built in this research work is not represented in the above table because RNN- CNN cannot be tested, for now, as a single library/plugin in python.

The Fig. 6 shows performance measurement graphical representation.

A sample data containing 700 tweets were used, out of which 550 were used for training while the remaining 150 were used for testing as presented succinctly in Table 4.2 below.

Table 2 Tested sample results

Machine Learning Model	Sample Tweet Tested	Bag of Words	Correctly Detected (Bullying/Aggression)	Not Detected	Accuracy %
Logistic Regression	700	220	147	73	66.82
Stochastic Gradient Descent	700	220	144	76	65.45
Bernoulli Naïve Bayes	700	220	141	79	64.09
Random Forest	700	220	122	98	55.45
K Nearest Neighbour	700	220	120	100	54.55
Linear Support Vector Machine	700	220	149	71	67.73
Recurrent Neural Network	700	220	210	10	95.45
Convolutional Neural Network	700	220	201	19	91.36

The pictorial representation of all the tested algorithms mentioned above with respect to their performance in terms of accuracy is presented in Fig.7 as follows.

From the evaluation chart, it is obvious that RNN in this context outperform other models in terms accuracy, which is one important criterion to look for when carrying out sentiment analysis of this type. It is also worth knowing that, in this research, both RNN and CNN are combined for maximum performance that

cannot be competed with by any singular machine learning model. Contextually, CNN outperforms other model when it comes image/video analysis while RNN is the best in terms text mining, which was why these two deep learning models were combined in this research work for maximum performance and accuracy.

Conclusion

Sentiment analysis, also known as opinion mining can be defined as the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. It is often driven by an algorithm, scoring the words used along with voice inflections that can indicate a person's underlying feelings about the topic of a discussion. Analyzing sentiments creates rooms for a more

objective interpretation of factors that are otherwise difficult to compute or typically measured subjectively.

This research work describes the design, implementation and applications of a Convolutional Neural Network-Recurrent Neural Network Based Cyber Bullying/Aggression detection system using Sentiment Analysis leveraging on real-Time Twitter Dataset. Combining sophisticated deep learning algorithm such as CNN and RNN provides a very robust and simplistic approach for detecting Cyber-bullying and aggression in real-time tweets using twitter Application Programming Interface thus enabling, for instance, parents to control the effects of Cyber-bullying or aggression on their kids, just in case.

The increase number of children or kids being bullied online and its effects on these children cannot be overemphasized and therefore, sequel to that, there is need for a robust Cyber-bullying detection system such as the one developed in this project work. Practically speaking, the accuracy of this system is astonishingly tacit and unmatched. Therefore, this system is highly recommended for use, especially by parents and teachers, to check the level of how much a kid has been bullied, thus that can be used to destigmatize such a child from that kind of experience. The system also has the capacity to cater for identity grabbing, which can also be used to put in check the bullies that will eventually reduce the number of their bullied counterparts. Identity grabbing is the ability of the analyzer to be able to identify and display the sender or originator of a particular tweet.

Future work may involve other dataset inclusion such as Instagram, WhatsApp and other social media in addition to the twitter dataset used in this project work. Thus, that would make the system more robust in power and accuracy since the power of any data mining algorithm depends solely on data.

Declarations

Availability of data and materials

Not applicable.

Funding

No funding yet

Acknowledgements

We would like to thank the anonymous reviewers for detailed comments and useful feedback.
Competing interests: The authors declare no competing interests.

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Figures

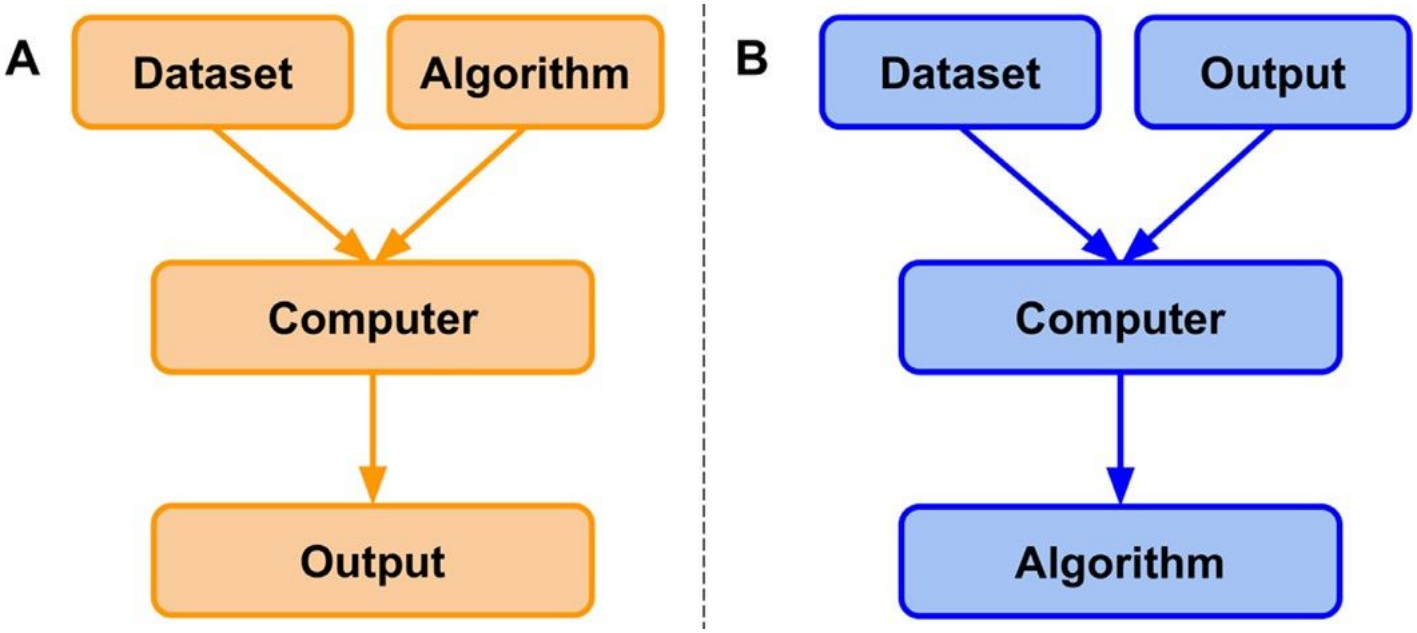

Figure 1

Conventional programming versus machine learning paradigm.Source (Rene, 2020)

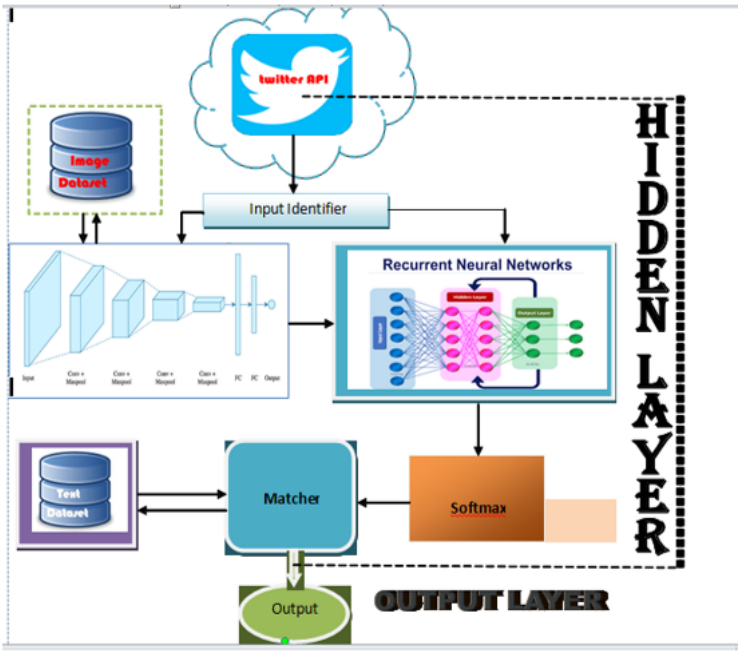

Figure 2

System Architecture

Figure 3

User Registration Page

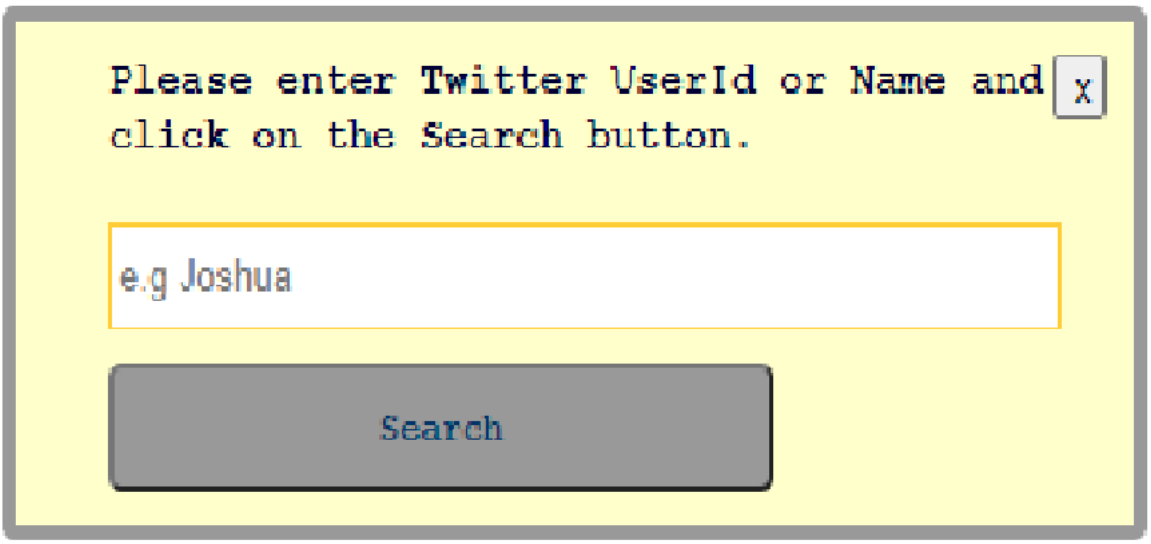

Figure 4

Search Page

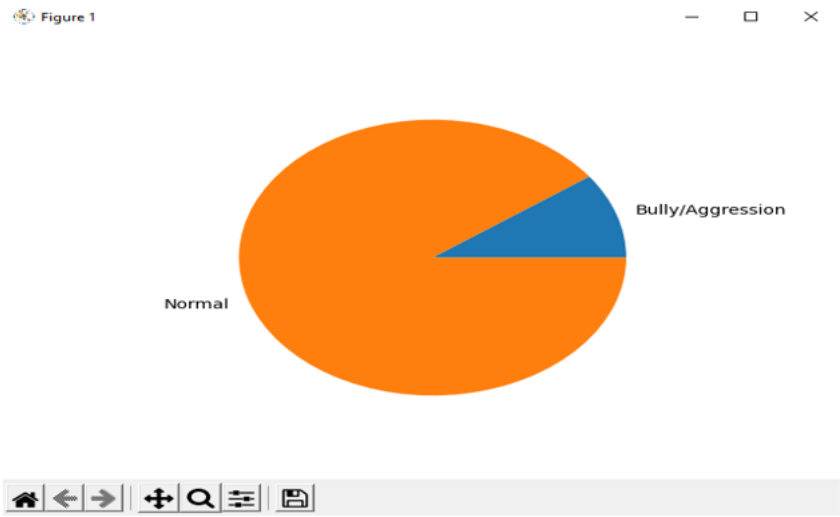

Figure 5

Output Display Page

Figure 6

Performance measurement graphical representation

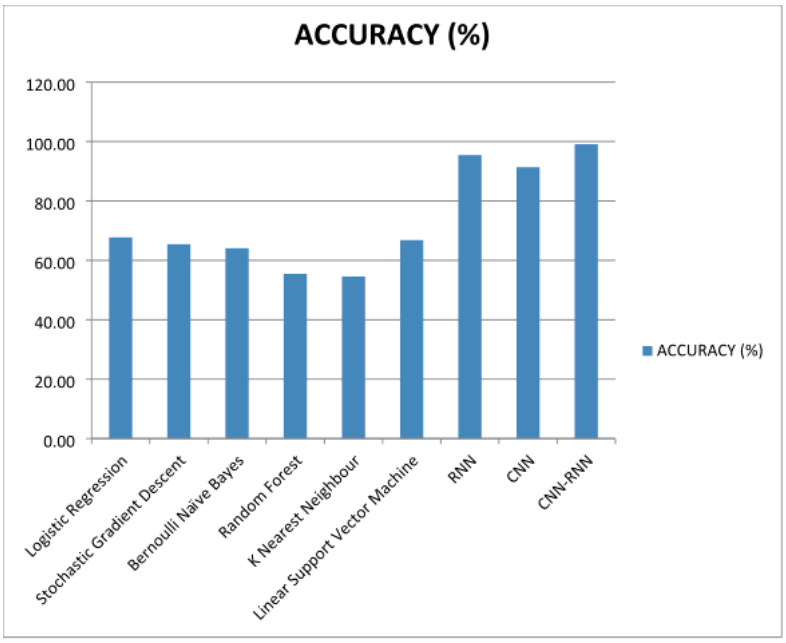

Figure 7

Performance Evaluation Chart