Sentiment Analysis of Customer Feedback for Commercial and Mobile Banking : A Machine Learning and Deep Learning Approach

A Thesis Report

Submitted in Partial Fulfillment of the Requirements
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In
Computer Science and Engineering

Submitted by

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Declaration of Originality

I am **Md. Ashaful Azim**, Id No – **CSE 01606587** student of B.Sc. (Computer Science and engineering), expressly declare that the thesis Dissertation titled "Sentiment analysis of customer feedback for commercial and mobile bank using machine and deep learning" which is submitted by me to the Computer Science and Engineering, Port City International University, in partial fulfilment of the requirement for the degree of Bachelor of Science, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associate ship, Fellowship or other similar title or recognition.

(Signature of the candidate)

Md. Ashaful Azim

Approval for Submission

The thesis dissertation titled “Sentiment Analysis of Customer Feedback for Commercial and Mobile Banking : A Machine and Deep Learning Approach” which is submitted by Md. Ashaful Azim, Id No. –CSE 01606587, Computer Science and Engendering, in partial fulfillment of the requirement for the award of the degree of Bachelor of Science, is a record of the thesis work carried out by the student under my supervision.

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Dedication

This is dedicated to my respected teachers along with my mother.

Acknowledgement

I outset to express our sincerest gratitude to **Mrs. Taofica Amrine** for her continuous guidance and mentorship that provided me throughout my thesis research. Also shown me the way to achieve our goals by describing all of the activities to be completed as well as the significance of this thesis.

My sense of obligation is also spread to the personnel and the Department of Computer Science and Engineering for their assistance in providing me with the resources needed to operate the process.

Finally I'd want to explicit my honor to my family and friends for their support.

Abstract

Sentiment analysis is a subsection of Natural Language Processing that purposes to abstract emotions or affections from text in a divergence of formats, including blogs, reviews, and social media and more. The purpose of this thesis is bank customer feedback analysis to show that a new process to analyze sentiment for commercial and mobile banking data. For this work we utilized some machine learning and deep learning algorithms in which we chosen Multinomial Naive Bayes and K-nearest neighbors as Machine learning algorithms converse Long short-term memory networks as deep learning . During this work purpose we used 101883 numbers of data . The final section of performance analysis accuracy of 86% and 91% has been obtained from two model of machine learning and the deep learning model achieve 93% accuracy respectively which was highest.

Keywords: Sentiment Analysis, Machine Learning, Deep Learning, Commercial Bank, Mobile bank

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Chapter 1

Introduction

Nowadays life is substantially linked with the existence of the web.The time of computerized data has turned into a momentous driver for banking organization's evolution and endurance. Data extraction in the virtual zone additive with its available appliances has set off some degree of contest among business administrators, in this way developing the comprehension of a financial idea accepted as "perfect contest market"[1]. As per ongoing experiment by Fintech Futures®, roughly 80% of banking information is unstructured. This presents a tremendous chance for banks, everything being equal, with two head applications: battling misrepresentation and further developing purchaser experience.

This inspection, the categorized bank customer opinions are classified through machine learning and deep learning algorithm for analyzing the sentiment of the people and improving mobile and commercial banking performance and quality.

1.1 Objectives

1. The world data is an impediment in separating sentiments, it hopes to separate notable data and information so in this work the objective presents a model that detects opinion from both mobile and business banking data.
2. To introduce a relative inspection among the used Machine Learning and Deep Learning algorithms.
3. To present a comparative analysis among the utilized Machine Learning and Deep Learning algorithms.

1.2 Motivation

In the present competitive banking industry, market division as a genuine vital option is vital on the off chance that players in the banking business are to accomplish consumer loyalty which can impact client unsparingness and productivity.

And the global financial crisis banks are investing much more in detecting risk, segment analysis also more reasons. So customer segmentation analysis is a structured process and facilitates effective acquisition and relation and intelligent marketing .

1.3 Natural Language Processing

Natural language processing endeavors to fabricate machines that comprehend and answer text or voice information — and answer with text or discourse of their own — similarly people do.

Normal language processing is a field of man-made consciousness in software engineering with collaboration among PCs and natural languages. With the mushroom development of machine learning, much natural language handling research has an extraordinary relationship with machine learning. Many machine learning calculations have been applied to regular language-handling tasks. Separating organized data from the intricacy of heterogeneous-described clinical reports is essentially tested, and the work got the outcomes with F1 scores more noteworthy than 95% utilizing machine learning, for instance, HMM model. Weng et al.[11] proposed the machine learning to arrange clinical notes to the clinical subdomain. They announced that the classifier of the convolutional intermittent brain network with word embeddings yielded the best execution on iDASH and MGH datasets with F1 scores of 0.845 and 0.870, separately. Basaldella et al.[12] proposed a crossover approach utilizing a two-stage pipeline with a machine-learning classifier consolidating a word reference approach, and they accomplished a general accuracy of 86a review of 60% on the named substance acknowledgment task. For helping with getting biomedical information, a flourishing of ontologies endeavored to address the intricacy of the biomedical ideas in text-mining region. The ontologies describe a wide assortment of natural ideas spreading over from science to medication. Moreover, they not just endeavor to catch the significance of a specific space in view of biomedical local area yet in addition are key component for information the board, and data integration. Ontologies and controlled vocabularies could work on the productivity and consistency of biomedical information curation, which has an extraordinary expanding interest in creating ontologies. Natural language handling (NLP) alludes to the part of computer science — and all the more explicitly, the part of man-made consciousness or AI — worried about empowering PCs to comprehend text and verbally expressed words similarly individuals can. NLP consolidates computational semantics — rule-based demonstrating of human language — with measurable, AI, and profound learning models. Together, these advancements empower PCs to handle human language as message or voice information and to 'comprehend' its full significance, complete with the speaker or essayist's expectation and opinion. NLP drives PC programs that decipher text starting with one language then onto the next, answer spoken orders, and sum up enormous volumes of text quickly — even progressively. There's a decent opportunity you've communicated with NLP as voice-worked GPS frameworks, computerized collaborators, discourse to-message correspondence programming, client support chatbots, and other purchaser comforts. In any case, NLP likewise assumes a filling part in big business arrangements that assist with smoothing out business tasks, increment representative efficiency, and improve on strategic business processes.

1.4 Sentiment Analysis

Sentiment analysis is the branch of natural language processing. Sentiment Analysis (SA) characterizes a survey record into a positive, neutral or negative sentiment. In this appearance, SA is equivalent to message assuming in that it utilizes particular sorts of high point in a survey to plan it into a specific classification. SA utilizes polarities like positive, natural or negative or a size of evaluations and depends on highlights about sentiment, influence, perspectives, and subjectivity. Presently Sentiment Analysis is the most widely recognized message characterization approach that investigations an approaching message and tells whether the fundamental opinion is positive, negative or negative.[2]

1.5 Mobile Banking

The present mobile banking is an application on your cell phone that is associated with the web and enrolled by telephone number. It is outfitted with a few security methodology delivered by each bank and you can perform banking capacities whenever, anyplace.

Moreover, mobile financial alludes to the utilization of a cell phone to complete exchanges. The assistance is given by a few monetary establishments, particularly banks. Also Mobile banking services can be categorized into the following: account information access, transactions, investments, support services, and content and news.Until this point in time, numerous monetary establishments and banks utilize the both SMS and applications to keep their clients educated regarding their record exercises or to convey cautions to clients with respect to conceivable misrepresentation and additionally updates and support of administration.

Banks give mobile banking administrations to their clients in the various ways recorded here:

- Mobile Banking over portable applications
- Mobile Banking over SMS
- Mobile Banking over Unstructured Supplementary Service Data (USSD)

Mobile Banking – Services Available

Mobile banking is valuable to clients in the accompanying ways:

(1) Access to Account Information

Data is power. Furthermore, hence, it is vital to realize your precise bank balance. This helps you in better administration of your assets. Furthermore, consequently, this is the essential mobile banking assistance given by any bank. You can actually take a look at the accompanying:

- View account balance
- Transaction history
- E-articulation of record
- Advance articulations

(2) Transactions

Making installments and moving cash starting with one record then onto the next is the most fundamental financial movement. In this manner it just appears to be legit that these are the most utilized and sought after versatile financial administrations. You can move assets to anybody by adding them as recipients or essentially by means of Unified Payments Interface or UPI.

1.6 Commercial Bank

A commercial bank is a monetary establishment that awards loans, accepts deposits, and offers fundamental financial items, for example, investment accounts and endorsements of store to organizations, rather than a retail bank that gives comparative monetary items to people. A commercial bank brings in cash fundamentally by giving various sorts of credits to clients and charging revenue [3].

The fundamental job of a commercial bank is to offer monetary types of assistance to organizations and organizations. Banks likewise guarantee financial dependability and the maintainable development of a nation's economy. To get more familiar with the various jobs accessible in a business bank[4]. A commercial bank carries out the accompanying role [5] .

1. Accepting Deposits

Accepting stores is probably the most established capacity of a commercial bank. At the point when banks began, they charged a commission for keeping cash for the benefit of the general population. With the progressions in the financial business throughout the long term and the productivity of the business, banks presently pay a limited quantity important to the contributors who keep cash with them. Be that as it may, contributors additionally bring about authoritative expenses to keep up with their records.

Banks acknowledge three sorts of stores. The first is the investment funds store for little savers who are paid revenue on their records. They can pull out their cash up to a restricted sum by composing a check.

The second sort of store is the ongoing record for individuals in business who can pull out their cash whenever without notice. Banks don't ordinarily pay revenue on stores held in current records. All things being equal, the record holders are charged an ostensible expense for the administrations delivered.

The last sort of store is the term or fixed store. Clients who have cash that they don't require for the following a half year or more can save in the decent record. The pace of interest paid increments with the length of the decent store. Clients can pull out the cash toward the finish of the concurred period by keeping in touch with the bank.

2. Advancing Credit Facilities

Advancing loans is a fundamental capacity of banks since it represents the most noteworthy level of income acquired every year. Banks for the most part offer present moment and medium-term credits from a level of the money stores at an exorbitant financing cost.

They don't give long haul supporting because of the need to keep up with the liquidity of resources. Prior to propelling advances to clients, banks think about the borrower's monetary status, business productivity, nature and size of the business, and capacity to reimburse the credit without default.

3. Credit Creation

While conceding loans to clients, [6] banks don't give the credit in real money to the borrower. All things being equal, the bank makes a store account from which the borrower can draw reserves. This permits the borrower to pull out cash with a money order as indicated by his requirements. By encouraging an interest store in the borrower's record without printing extra cash, the bank expands how much cash available for use.

4. Agency Functions

Commercial banks act as specialists of their clients by aiding them in gathering and paying checks, profits, premium warrants, and bills of trade. Additionally, they pay insurance installments, service bills, lease, and different charges in the interest of their clients.

Banks additionally exchange offers, protections, and debentures, and they offer warning types of assistance for clients that need to trade these speculations. In property organization, business banks go about as legal administrators and agents of the bequest for the benefit of their clients. Banks charge an ostensible expense for the organization capacities performed in the interest of their clients.

1.7 Data Mining

Data or Information mining is the method involved with figuring out enormous informational collections to distinguish examples and connections that can assist with taking care of business issues through information investigation. Information mining strategies and apparatuses empower undertakings to anticipate future patterns and settle on more-informed business choices[7].

Data mining is the most common way of finding peculiarities, examples and connections inside enormous informational collections to foresee results. Utilizing an expansive scope of methods, you can utilize this data to increment incomes, cut costs, further develop client connections, lessen dangers and that's just the beginning. Data mining allows you to: (1) Sift through all the chaotic and repetitive noise in your data. (2) Understand what is relevant and then make good use of that information to assess likely outcomes. (3) Speed up the speed of pursuing informed choices.

There are various essential data mining strategies to consider while entering the data field, however the absolute most pervasive techniques incorporate bunching, information cleaning, affiliation, information warehousing, AI, information perception, arrangement, brain organizations, and expectation. Every one of these methods contains a significant part of data mining.

1.8 Machine Learning

Machine learning is a part of artificial intelligence (AI) and computer science which centers around the utilization of information and calculations to impersonate the way that people learn, progressively working on its exactness[8]. Machine learning is a significant part of the developing field of information science. Using measurable techniques, calculations are prepared to make characterizations or expectations, uncovering key bits of knowledge inside information mining projects. These bits of knowledge in this manner drive decision making inside applications and organizations, in a perfect world influencing key development measurements. As large information proceeds to extend and develop, the market interest for information researchers will increment, expecting them to aid the distinguishing proof of the most significant business questions and in this manner the information to respond to them.

These are three types of machine learning

1. supervised learning
2. unsupervised learning
3. reinforcement learning

1.9 Machine Learning Classification

Characterization is a sort of regulated learning task in the field of machine learning. The motivation behind characterization is to take in information focuses that have some number of the significant highlights and utilize these elements to anticipate what class, out of the picked classes of interest, the model has a place with.

Classification undertakings can be either parallel in nature, with only a couple of classes, or multi-class. Instances of characterization issues incorporate discourse acknowledgment (a parallel issue: either discourse or non-discourse), report grouping, diagnosing clinical side effects, and spam acknowledgment.

1.10 Deep Learning

Deep learning is a machine learning procedure that trains PCs to do what falls into place without a hitch for people: advance as a visual demonstration. Deep learning is a critical innovation behind driverless vehicles, empowering them to perceive a stop sign, or to recognize a person on foot from a light post. It is the way to voice control in purchaser gadgets like telephones, tablets, TVs, and without hands speakers. Profound learning is definitely standing out enough to be noticed recently and for good explanation. It's accomplishing results that were impractical previously.[9]

In deep learning , a PC model figures out how to perform characterization undertakings straightforwardly from pictures, text, or sound. Profound learning models can accomplish best in class exactness, some of the time surpassing human-level execution. Models are prepared by utilizing an enormous arrangement of marked information and brain network structures that contain many layers[10].

Deep learning networks learn by discovering intricate structures in the data they experience. By building computational models that are composed of multiple processing layers, the networks can create multiple levels of abstraction to represent the data.

1.11 Thesis Organization

The thesis is organized as follows:

Already in the first chapter several topics have been discussed including sentiment analysis, data mining, banking and more important topics.

- **Chapter 2:** Literature Review : gives an overview of the sentiment analysis and the research concluded in this field.
- **Chapter 3:** Methodology: presents the proposed technique and describe a hybrid model and how to evaluate sentiment and system score.
- **Chapter 4:** Hardware Implementation And Toolkit : Describe about used programming languages,tools, IDE's and all .
- **Chapter 5:**: Results And Performance Analysis: presents there experimental results we achieved through comparing to all proposed model.
- **Chapter 6:** Conclusion and Future Work: It concludes the thesis and mentions the possible direction for future work

Chapter 2

Literature Review

In spite of the fact that sentiment analysis and opinion mining became one of the most significant sources in decision making in business still a few difficulties need further consideration. In the accompanying, discuss about the connected work with sentiment analysis and challenges:

Sentiment Analysis (additionally called Opinion Mining, Sentiment characterization, subjectivity investigation, valuation extraction) is a computational investigation of reviews, sentiments, suppositions, assessments, perspectives, abstract, sees, emotions, and communicated in the text. Sentiment analysis is generally utilized for online reviews and web-based entertainment for an assortment of applications, from advertising to client assistance. Sentiment Analysis or rather the positive/negative characterization relies upon the utilization of datasets and classifiers. The archive applies gathering into two sets: positive and negative. Most of the lexicon-based sentiment analysis strategies or Machine Learning [8].

Ekanata and Budi direct comparative Analysis on mobile application survey characterization utilizing the machine approach [11]. They direct an application client opinion investigation in light of surveys, evaluations, and length audits. The classifier calculations they use are credulous Bayes, choice trees, SVM, and calculated relapse. The normal of the f-measure of every calculation is 0.85 for strategic relapse and 0.849 for SVM and Naive Bayes. From these outcomes, it very well may be inferred that there is no tremendous distinction between each model delivered.

In contemporary organizations, client relationship the management (CRM) has turned into a principal instrument for a benefit and not-for-profit business associations to connect with and hold a forthcoming and existing client for business development and advancement [10]. Along these lines, for business to acquire significant data for relationship the executives, text mining has become basic to numerous organizations particularly computerized advertising in the 21st hundred years. Considering the banks item and one more assistance corresponding to additional complex clients, it has become vital that banks and other monetary establishments decide the variables which are appropriate to the client's determination interaction. The component determinants from clients act as a signal for CRM .

Notwithstanding, in [12] it was contended that enormous information examination in contemporary advertising research isn't simply connected with exceptionally digitalized performing business yet additionally think about new businesses and miniature to little to-medium firms that look to confront difficulties of market advancement. Likewise, business knowledge and investigation has arisen as one of the significant areas of study for the two professionals and specialists with respect to the level of effect of information related issues to be addressed in present day business associations. As indicated by [13] text mining of customer's assessment in the web-based stages is seen as a center part of Business Intelligence Research (BIR) by giving uncover information which affects business processes. The writing on web related substances investigated that few worldwide organizations and IT patterns have supported to shape over a significant time span BIR headings. These advancements have worldwide versatile, high-speed network associations, worldwide production network, what's more, supplementing with re-appropriating have made a gigantic a chance for IT progression [14] [6] .

To keep up with the exclusive requirements of safety in the midst of the mind-boggling progression of enormous financial information and the quickly developing scale and intricacy of digital wrongdoings, specialists have been investigating progressed DM strategies for successfully distinguishing surprising misrepresentation conduct. Note that a current survey that designated charge card handling can be found in [15]. According to an interior point of view, the overview information of bank representatives in India are gathered in [16] to break down their discernment's with respect to misrepresentation.

The fundamental information mining undertakings are characterization (or straight out expectation), relapse (or numeric forecast), grouping, affiliation rule mining, and inconsistency identification. Among these information mining undertakings, characterization is the most often involved one in the financial area [17], which is trailed by grouping. Some financial applications [18] [19] have utilized more than one information mining procedures, among which grouping before characterization has shown adequate proof of both prevalence and appropriateness.

In the field of ensemble methods, the main idea is to combine a set of models (base classifiers) in order to obtain a more accurate and reliable model in comparison with what a single model can achieve. The methods used for building upon an ensemble approach are many, and a categorization is presented in [20]. This classification is based on two main dimensions: how predictions are combined (rule based and meta learning), and how the learning process is done (concurrent and sequential).

Managing class imbalance issue, different solutions have been proposed in the writing. Such techniques can be for the most part gathered under two distinct methodologies: (I) utilization of an information prepossessing step and (ii) changing existing strategies. The principal approach centers around adjusting the dataset, which might be done either by expanding the quantity of minority class models (over-sampling) or diminishing the quantity of greater part class models (under-sampling). In the writing, manufactured minority over-sampling procedure (SMOTE) [21] is ordinarily utilized as an over-testing strategy. As an elective methodology, a few investigations (i.e., [22]) center around changing the current characterization calculations to make them more compelling while managing imbalanced information. Not at all like these investigations, this paper proposes an original methodology (class-based weighting approach) take care of imbalanced data issue.

Chapter 3

Methodology

This chapter gives a broad overview of the methodology of this research. All the data collection, prepossessing, feature extraction, system architecture and performance analysis matrices are explained in this chapter. Figure 3.9 shows the proposed methodology.

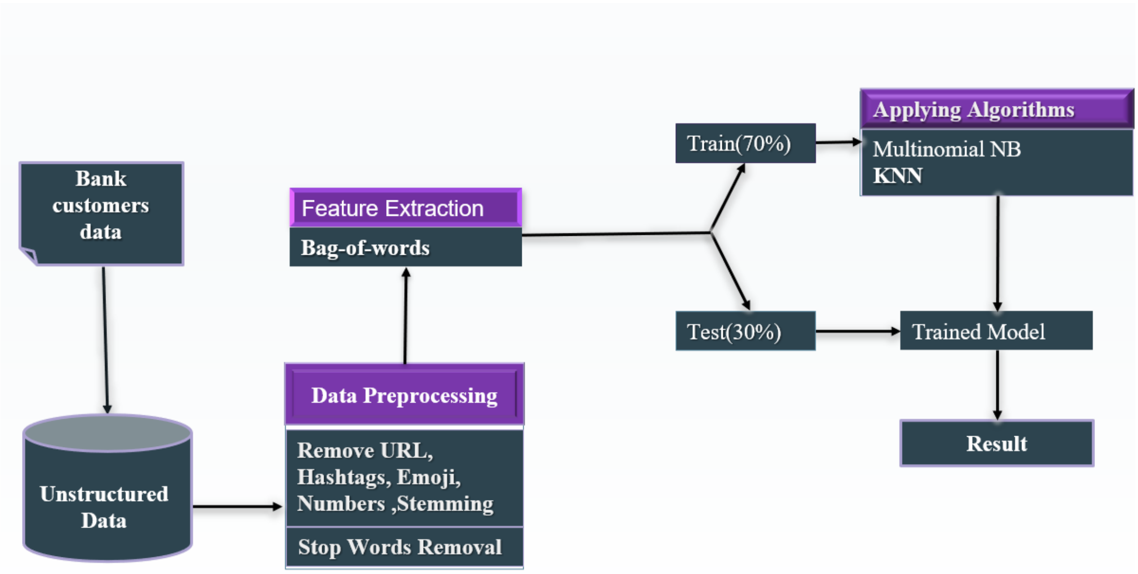


Figure 1. : *Proposed Methodology.*

3.1 Data Collection

The data used in this research was collected from the comment sections of a commercial website (49288) and review section of mobile banking apps(53082).Where 63168 data personally scraped and the remaining 39191 data were gathered from the website Customer Financial Protection Bureau(CFPB) . A total of 101883 unique texts were collected containing in English.

Figure 2 shows the code segment of that searches for a particular application using a given query. The query can be the review of this application.

```
[ ] from google_play_scraper import app

    import pandas as pd

    import numpy as np
```

```
[ ] from google_play_scraper import Sort, reviews_all
```

```
from google_play_scraper import Sort, reviews_all


us_reviews = reviews_all(
      'com.bKash.customerapp',
    sleep_milliseconds=0, # defaults to 0
    lang='en', # defaults to 'en'
    country='us', # defaults to 'us'
    sort=Sort.NEWEST, # defaults to Sort.MOST_RELEVANT
)
```

```
[ ] df_busu = pd.DataFrame(np.array(us_reviews),columns=['review'])
    df_busu = df_busu.join(pd.DataFrame(df_busu.pop('review').tolist()))
    df_busu.head()
```

Figure 2. *shows the code segment that iterates through the review section of the scraps the required information.*

After completed scrape Figure 3 shows some snaps of the dataset which prepared for this work:

	Reviews	Level	Sentiment
0	Make a version of dark theme	Mobile banking	Neutral
1	I can easily make my urgent transactions using...	Mobile banking	Positive
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative
4	Would you please give me the details of the ho...	Commercial Banking	Neutral

Figure 3. : *Visualization of Dataset* .

3.2 Data Annotation

After the data assortment process, sentiment has been added manually on this dataset as Positive, Neutral or Negative [23]. Figure 4 and 5 shows the per class information dissemination of every one of the dataset.

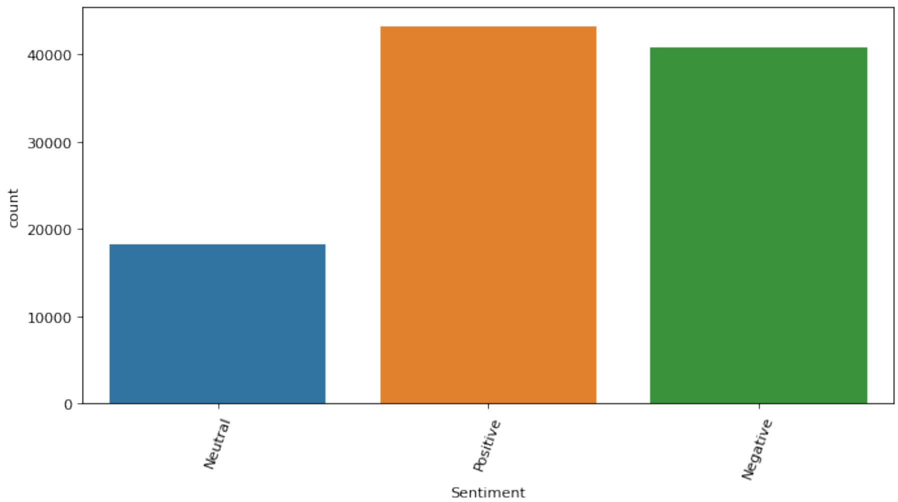


Figure 4. : *Visualization of Dataset with two classes.*

In this figure 4 shows data with three types of sentiment positive , negative and neutral were the amount of total positive data are 41667 and 45982 data are negative and less 14721 amount of data are neutral .

In this section, shows the three sentiment positive negative and neutral of two classes separately.

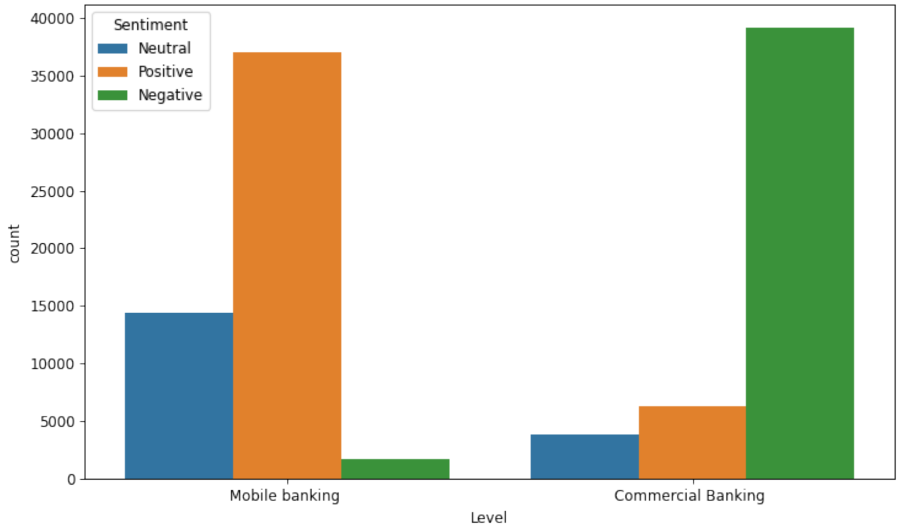


Figure 5. : *Visualization of Dataset with three classes.*

The two types of classes are mobile banking and commercial banking .Noticed that in mobile banking data the number of positive data is more than neutral and negative other part in commercial banking data were negative amount of data is more than positive and neutral data .

3.3 Data Cleaning

As the dataset contained a great deal of commotion, cleaning the data was fundamental. The cleaning process incorporates accentuation marks evacuation, digits expulsion, emoji evacuation, managing out lengthened words, interfaces, url's, client labels and notices evacuation. Figure 6, 7, 8, 9, 10 and 11, shows the utilized to clean texts individually. data analysis requires successfully cleaned data to deliver precise and dependable bits of knowledge. Be that as it may, clean data has a scope of different advantages, as well:

(1) Staying coordinated: Today's organizations gather bunches of data from clients, clients, item clients, etc. These subtleties incorporate all that from addresses and telephone numbers to bank subtleties and that's only the tip of the iceberg. Cleaning this information consistently implies keeping it clean. It can then be put away more successfully and safely

(2) Further developing efficiency: Regularly cleaning and it is immediately cleansed to refresh data implies maverick data. This recoveries groups from being required to swim through old information bases or archives to find what they're searching for.

(3) Developed mapping: Increasingly, associations are hoping to further develop their interior data foundations. For this, they frequently recruit data investigators to complete data demonstrating and to construct new applications. Having clean information from the very beginning makes it far more straightforward to examine and plan, implying that a strong data cleanliness plan is a reasonable measure.

Present the raw dataset after leveled with sentiment is shows blow

	Reviews	Level	Sentiment
0	Make a version of dark theme	Mobile banking	Neutral
1	I can easily make my urgent transactions using...	Mobile banking	Positive
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative
4	Would you please give me the details of the ho...	Commercial Banking	Neutral
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative
6	Didn't receive enough information to verify debt	Commercial Banking	Negative
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive
8	No good App	Mobile banking	Negative
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive

Figure 6. : *Visualization of Dataset.*

3.3.1 Remove Punctuation

we need to carefully choose the list of punctuation which we are going to discard based on the use case.Present the dataset blew after removing punctuation marks as part of prepossessing

	Reviews	Level	Sentiment	clean_review
0	Make a version of dark theme	Mobile banking	Neutral	Make a version of dark theme
1	I can easily make my urgent transactions using...	Mobile banking	Positive	I can easily make my urgent transactions using...
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative	My Sister Going through Tough time Collecting ...
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative	This app is very disappointed for me coz maxim...
4	Would you please give me the details of the ho...	Commercial Banking	Neutral	Would you please give me the details of the ho...
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative	While entering pinit says wrongbut i tried 247...
6	Didn't receive enough information to verify debt	Commercial Banking	Negative	Didnt receive enough information to verify debt
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive	One can easily pay the utility bill and variou...
8	No good App	Mobile banking	Negative	No good App
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive	So irritating Apps open hoi na Onek din dhora ...

Figure 7. : *Visualization of Dataset after removing punctuation marks.*

3.3.2 Lowercase conversion

Converting all your data to lowercase helps in the process of prepossessing and in later stages in the NLP application Present the dataset blew after converting all the data to lowers as part of prepossessing

	Reviews	Level	Sentiment	clean_review
0	Make a version of dark theme	Mobile banking	Neutral	make a version of dark theme
1	I can easily make my urgent transactions using...	Mobile banking	Positive	i can easily make my urgent transactions using...
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative	my sister going through tough time collecting ...
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative	this app is very disappointed for me coz maxim...
4	Would you please give me the details of the ho...	Commercial Banking	Neutral	would you please give me the details of the ho...
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative	while entering pinit says wrongbut i tried 247...
6	Didn't receive enough information to verify debt	Commercial Banking	Negative	didnt receive enough information to verify debt
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive	one can easily pay the utility bill and variou...
8	No good App	Mobile banking	Negative	no good app
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive	so irritating apps open hoi na onek din dhora ...

Figure 8. : *Visualization of Dataset after converting to lowers.*

3.3.3 Tokenization

Tokenization is quite possibly the most well-known task with regards to working with text data.Tokenization is basically parting an expression, sentence, passage, or a whole message record into more modest units, like individual words or terms. Every one of these more modest units are called tokens Present the dataset blew after tokenizing as part of prepossessing

	Reviews	Level	Sentiment	clean_review
0	Make a version of dark theme	Mobile banking	Neutral	[make a version of dark theme]
1	I can easily make my urgent transactions using...	Mobile banking	Positive	[i can easily make my urgent transactions usin...
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative	[my sister going through tough time collecting...
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative	[this app is very disappointed for me coz maxi...
4	Would you please give me the details of the ho...	Commercial Banking	Neutral	[would you please give me the details of the h...
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative	[while entering pinit says wrongbut i tried 24...
6	Didn't receive enough information to verify debt	Commercial Banking	Negative	[didnt receive enough information to verify debt]
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive	[one can easily pay the utility bill and vario...
8	No good App	Mobile banking	Negative	[no good app]
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive	[so irritating apps open hoi na onek din dhora...

Figure 9. : *Visualization of Dataset after tokenizing.*

3.3.4 Stop word removal

Stop word removal is one of the most normally utilized preprocessing ventures across various NLP applications. The thought is basically eliminating the words that happen ordinarily across every one of the records in the corpus. Regularly, articles and pronouns are for the most part named stop words. Present the dataset blew after removing stop word as part of prepossessing

	Reviews	Level	Sentiment	clean_review
0	Make a version of dark theme	Mobile banking	Neutral	[make a version of dark theme]
1	I can easily make my urgent transactions using...	Mobile banking	Positive	[i can easily make my urgent transactions usin...
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative	[my sister going through tough time collecting...
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative	[this app is very disappointed for me coz maxi...
4	Would you please give me the details of the ho...	Commercial Banking	Neutral	[would you please give me the details of the h...
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative	[while entering pinit says wrongbut i tried 24...
6	Didn't receive enough information to verify debt	Commercial Banking	Negative	[didnt receive enough information to verify debt]
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive	[one can easily pay the utility bill and vario...
8	No good App	Mobile banking	Negative	[no good app]
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive	[so irritating apps open hoi na onek din dhora...

Figure 10. : *Visualization of Dataset after removing stop word.*

3.3.5 Stemming

Stemming is the most common way of diminishing a word to its promise stem that fastens to postfixes and prefixes or to the underlying foundations of words known as a lemma. Stemming is significant in natural language understanding out (NLU) and natural language processing (NLP). Stemming is a piece of etymological studies in artificial intelligence (AI) data recovery and extraction. Stemming and AI information extricate significant data from immense sources like large information or the Internet since extra types of a word connected with a subject might should be looked to obtain the best outcomes. Stemming is likewise a piece of inquiries and Internet web crawlers. Present the dataset blew after applied stemming process as part of prepossessing

	Reviews	Level	Sentiment	clean_review
0	Make a version of dark theme	Mobile banking	Neutral	[make a version of dark them]
1	I can easily make my urgent transactions using...	Mobile banking	Positive	[i can easily make my urgent transactions usin...
2	My Sister Going through Tough time Collecting ...	Commercial Banking	Negative	[my sister going through tough time collecting...
3	This app is very disappointed for me, coz maxi...	Mobile banking	Negative	[this app is very disappointed for me coz maxi...
4	Would you please give me the details of the ho...	Commercial Banking	Neutral	[would you please give me the details of the h...
5	While entering pin,it says wrong..but i tried ...	Mobile banking	Negative	[while entering pinit says wrongbut i tried 24...
6	Didn't receive enough information to verify debt	Commercial Banking	Negative	[didnt receive enough information to verify debt]
7	One can easily pay the utility bill and variou...	Commercial Banking	Positive	[one can easily pay the utility bill and vario...
8	No good App	Mobile banking	Negative	[no good app]
9	So irritating.. Apps open hoi na.. Onek din dh...	Mobile banking	Positive	[so irritating apps open hoi na onek din dhora...

Figure 11. : *Visualization of Dataset after stemming.*

3.4 Feature Extraction

Highlight extraction is the method involved with extricating significant data from information. As the calculations might not deal with text based information, significant mathematical highlights at any point need to be extricated from the dataset[**10**]. To play out the component extraction from all the datasets, two interaction were utilized. One of the interaction is Bag-of-words which was utilized for AI calculations and the other was word installing which was utilized for Deep Learning algorithms.

Bag-of-words

Bag of words is a Natural Language Processing strategy of text modelling. In specialized terms, we can say that it is a technique for feature extraction with text information. This approach is a straightforward and adaptable approach to removing highlights from records.

A bag of words is a portrayal of text that depicts the event of words inside a record. We simply monitor word counts and dismissal the linguistic subtleties and the word request. It is known as a "bag" of words on the grounds that any data about the request or design of words in the record is disposed of. The model is just worried about whether realized words happen in the report, not where in the archive.

Figure 13 shows the python code that was used to calculate Bag of Word

```
[31] from sklearn.feature_extraction.text import CountVectorizer
     cv = CountVectorizer(max_features = 1500)
     X = cv.fit_transform(X).toarray()
```

Figure 12. *: Code to calculate Bag-of-words.*

Example with prepossessing:

Sentence 1: ”Make a version of dark theme”

Sentence 2: “I can easily make my urgent transactions using bKash app. Thanks to all the members of bKash team.”

Step 1: Convert the above two sentences into lower case as the case of the word does not hold any information.

Step 2: Remove special characters and stopwords from the text. Stopwords are the words that do not contain much information about text like ‘is’, ‘a’,’the, and, number and many more’.

Step 3: Go through all the words in the above text and make a list of all of the words in our model vocabulary.

1. app,
2. bkash,
3. dark,
4. easily
5. make
6. members
7. team
8. thanks
9. theme
10. transactions
11. urgent
12. using
13. version

After applying Bag-of-words model result shown blew:

	app	bkash	dark	easily	make	members	team	thanks	theme	transactions	urgent	using	version
0	0	0	1	0	1	0	0	0	1	0	0	0	1
1	1	2	0	1	1	1	1	1	0	1	1	1	0

Figure 13. *: Outputs of Bag-of-words.*

3.5 Oversampling

Random oversampling involves randomly selecting examples from the minority class, with replacement, and adding them to the training dataset. Because of absence of equilibrium data as per sentiment oversampling has been applied. After applied oversampling changed dataset is displayed in figure underneath

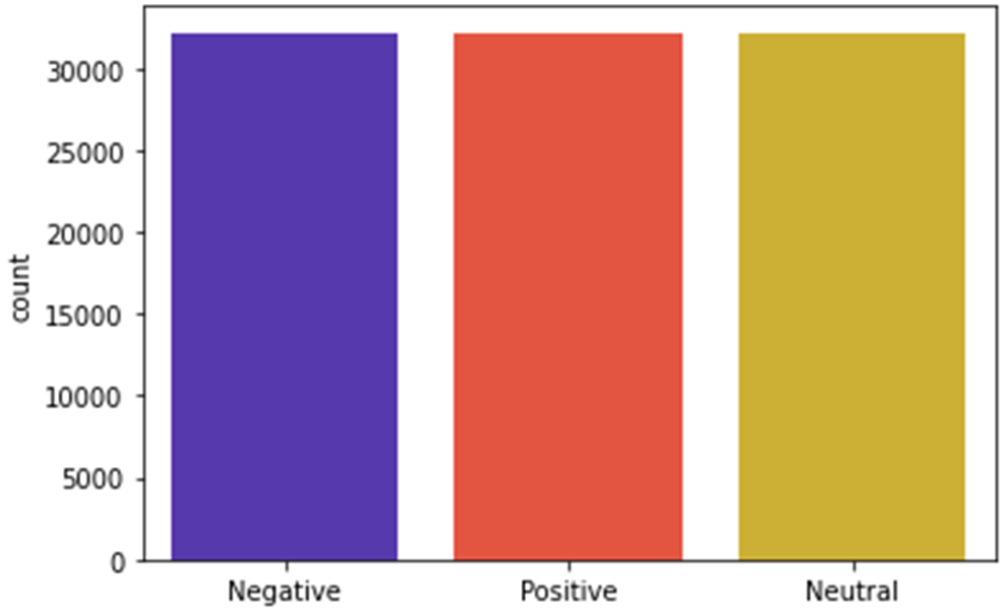


Figure 14. *: Dataset after over sampling*

The unevenness of the dataset should be dealt with prior to preparing a model. There are different procedures to deal with class balance, some of them being Oversampling, Under sampling, or a mix of both. We have previously seen imbalance data on three types of sentiment in out dataset. After oversampling the problem of imbalance data are followed by an equal number of data of three types of sentiment positive negative and neutral . Here can be seen that where the total data of negative are 45982, now there are 30,000 plus, on the other hand previously there are only 14000 neutral data but now it has become also 30000 plus as similar as negative and positive .

3.6 Machine Learning Algorithms

This segment presents a prologue to the Machine Learning algorithms that were utilized in this exploration.

3.6.1 Multinomial Naive Bayes

The Multinomial Naive Bayes algorithm is a probabilistic learning approach popular in Natural Language Processing (NLP). The program guesses the tag of a text, such as an email or a newspaper story, using the Bayes theorem[**13**]. It calculates each tag's likelihood for a given sample and outputs the tag with the highest probability. Equation 3.4 is used to calculate the probability of each tag.

```
#MULTINOMIAL NB
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
nb.fit(X_train_s,y_train_s)

MultinomialNB()
```

Figure 15. *: Code for training the Multinomial Naive Bayes algorithm*

3.6.2 K-Nearest Neighbor

K-Nearest Neighbor is one of the most simplest Machine Learning algorithms in light of Supervised Learning procedure. K-NN calculation accepts the comparability between the new case/information and accessible cases and put the new case into the classification that is generally like the accessible classifications. K-NN algorithms stores every one of the accessible information and characterizes another information point in light of the comparability. This implies when new information shows up then it tends to be effortlessly characterized into a well suite classification by utilizing K-NN algorithms . K-NN algorithms can be utilized for Regression as well with respect to Classification however for the most part it is utilized for the Classification issues. K-NN is a non-parametric algorithms , and that implies it makes no supposition on fundamental information. It is likewise called a lethargic student algorithms since it doesn't gain from the preparation set promptly rather it stores the dataset and at the hour of characterization, it plays out an activity on the dataset. KNN algorithms at the preparation stage simply stores the dataset and when it gets new information, then, at that point, it characterizes that information into a classification that is much like the new information.

Assume there are two classifications, i.e., Category An and Category B, and we have another information point x1, so this information point will lie in which of these classifications. To take care of this sort of issue, we really want a K-NN algorithm. With the assistance of K-NN, we can undoubtedly distinguish the classification or class of a specific dataset. Consider the underneath outline :

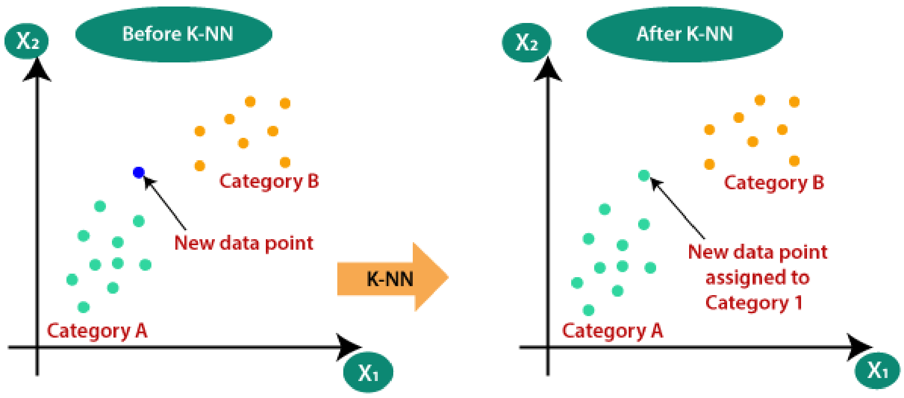


Figure 16. : *Changes views of after applying K-Nearest Neighbor*

The K-NN working can be explained on the basis of the below algorithm:

1. Select the number K of the neighbors,
2. Calculate the Euclidean distance of K number of neighbors
3. Take the K nearest neighbors as per the calculated Euclidean distance.
4. Among these k neighbors, count the number of the data points in each category.
5. Among these k neighbors, count the number of the data points in each category.

Code emnpliment of K-NN algorithm :

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=20)
knn.fit(X_train,y_train)
predict = knn.predict(X_test)
print(classification_report(y_test,predict))
```

Figure 17. : *Code for training the K-Nearest Neighbor*

3.7 Deep Learning Algorithms

This section presents an introduction to the Deep Learning algorithms that were used in this research.
Text classification is one of the famous tasks in NLP that permits a program to classify free-text records based on pre-defined classes. The classes can be founded on topic, genre, or sentiment. Today's emergence of huge digital documents makes the text classification task more urgent, especially for companies to maximize their workflow or even profits.
As of late, the progress of NLP research on text classification has arrived at the cutting edge (SOTA). It has accomplished terrific outcomes, showing Deep Learning methods as the cutting-edge technology to perform such tasks.
Subsequently, the need to assess the presentation of the SOTA deep learning models for text classification is essential not only for scholastic purposes but also for AI experts or professionals that need direction and benchmark on comparable projects.

3.7.1 Long Short Term Memory (LSTM)

The LSTM is a simple RNN that has been extended. It remembers dependencies across long gaps and mitigates the problem of disappearing gradients. The forget gate is the LSTM's middle layer, and it determines which data needs to be normalized and which data needs to be forgotten. An input gate modulates the inputs of each memory cell, whereas an output gate modulates the output.

Figure 3.17 shows the layer combination of the LSTM architecture.

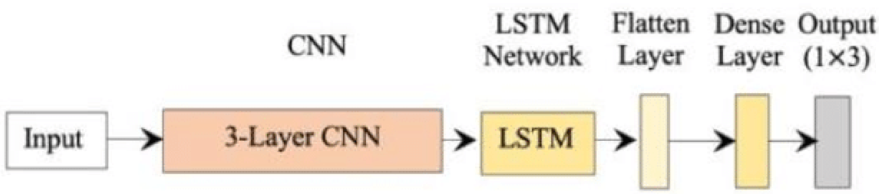


Figure 18. : *Layer combination of LSTM*

The dropout layers of this architecture had 30% dropout rate and the LSTM layer had 500 neurons. The dense layer was added with 'sigmoid' activation function. Finally the LSTM model was compiled with 'binary crossentropy' as loss function and 'adam' optimizer to reduce the loss. The model was trained for 10 epochs. Figure 18, 19 and 20 shows the python implementation of LSTM and Figure 3.21 shows the model summery

```python
import keras.backend as K
from keras.models import Sequential
from keras.layers import Dense,Embedding,Conv1D,MaxPooling1D,LSTM
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

batch_size = 128
epochs = 5
```

Figure 19. : *Code to implement LSTM*

```python
def get_model(max_features, embed_dim):
    np.random.seed(seed)
    K.clear_session()
    model = Sequential()
    model.add(Embedding(max_features, embed_dim, input_length=X_train.shape[1]))
    model.add(Conv1D(filters=32, kernel_size=3, padding='same', activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Conv1D(filters=32, kernel_size=3, padding='same', activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
    model.add(LSTM(100, dropout=0.2, recurrent_dropout=0.2))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    print(model.summary())
    return model
```

Figure 20. : *Code to implement LSTM*

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 30, 100)           2000000

 conv1d (Conv1D)             (None, 30, 32)            9632

 max_pooling1d (MaxPooling1D  (None, 15, 32)           0
 )

 conv1d_1 (Conv1D)           (None, 15, 32)            3104

 max_pooling1d_1 (MaxPooling  (None, 7, 32)            0
 1D)

 lstm (LSTM)                 (None, 100)               53200

 dense (Dense)               (None, 3)                 303

=================================================================
Total params: 2,066,239
Trainable params: 2,066,239
Non-trainable params: 0
```

Figure 21. : *Model summery of LSTM*

At figure 21, basically the explanation there are such countless boundaries for a LSTM model is on the grounds that you have lots of information in your model and a huge number should be prepared to fit the model.

Dropout layers don't have boundaries since there are no loads in a dropout layer. Each of the a dropout layer does is give a percent opportunity that a neuron won't be incorporated during testing. For this situation, you've picked half. Past that, pretty much nothing remains to be designed in a dropout layer.

First and foremost, at a fundamental level, the result of a LSTM at a specific moment is dependent on three things:

1. The current long-term memory of the network — known as the cell state
2. The output at the previous point in time — known as the 3. previous hidden state
3. The input data at the current time step

LSTMs utilize a progression of 'gates' which control how the data in a succession of information comes into, is put away in and leaves the organization. There are three entryways in a run of the mill LSTM; neglect door, input entryway and result entryway. These entryways can be considered channels and are each their own brain organization

Chapter 4

Hardware Implementation And Toolkit

4.1 Tools and Technology

The following tools are used in the implementation of the proposed system where all code was executed by python and google colab was used as the web integrated development environment :

1. Python
2. Google Colab

4.1.1 Python

Instruments and Devices Python is A perceived, object-oriented programming language very much like PERL, that has acquired quality because of its unmistakable linguistic structure and comprehensibility. Python is professed to be relatively direct to find out and moveable, and that implies its assertions are perceived in a very assortment of employable frameworks, as well as UNIX-based frameworks, Macintosh OS, MS-DOS, OS/2, and various adaptations of Microsoft Windows 98. Python was made by Guido van Rossum, a previous inhabitant of the Kingdom of The Netherlands, whose most loved satire bunch at the time was Monty Python's Flying Carnival. The ASCII text document is uninhibitedly available and open for alteration and usage. Python incorporates a significant assortment of clients.The accompanying libraries of python was utilized all through this exploration.

- **Numpy:** NumPy, which represents Numerical Python, is a library comprising of multi-layered cluster objects and an assortment of schedules for handling those exhibits. Utilizing NumPy, numerical and intelligent procedure on exhibits can be performed. NumPy is a Python bundle. which was made in 2005 by Travis Oliphant. It is an open source task, and anybody can utilize it unreservedly.

- **Pandas:** Pandas is an open source Python bundle that is generally broadly utilized for information science/information investigation and AI assignments. It is based on top of another bundle named Numpy, which offers help for multi-layered clusters.
- **Scikit-learn:** Scikit-learn is an open source Machine Learning Python bundle that offers usefulness supporting supervised and unsupervised learning. Also, it gives tools to show improvement, determination, and assessment as well as numerous different utilities including information pre-processing usefulness.
- **Tensorflow:** TensorFlow is a Python library for quick mathematical processing made and delivered by Google. An establishment library can be utilized to make Deep Learning models straightforwardly or by utilizing covering libraries that improve on the cycle based on top of TensorFlow.

4.1.2 Google Colab

Colaboratory, or "Colab" for short, is an item from Google Research. Colab permits anyone to compose and execute inconsistent python code through the program, and is particularly appropriate to AI, information investigation and instruction. All the more in fact, Colab is a facilitated Jupyter notebook pad administration that requires no arrangement to use, while giving access for nothing to registering assets including GPUs.

4.2 Equipment Implementation

The following hardware tools were use for implementation:

1. Inter core i5 processor with 1.60-3.90GHz clock speedn
2. 12GB ram
3. Nvidia MX250 Graphics with 2GB memory
4. 64 bit windows 10 operating system

RAM is usually used for temporarily storing data or files to be used easily and quickly. In a general-configured CPU, the RAM is like 4, 6, or 8 GB. When the dataset to train a model is small in size, it fits easily into the system RAM. But, if the dataset is large, system RAM is not enough to train a model with this large dataset. To solve the problem, Google Colab provides 12 GB of virtual memory free of charge.

Chapter 5

Results And Performance Analysis

This section centers around breaking down the boundaries with regards to disarray framework, exactness, accuracy, review, f1-scores and roc region and introducing the relative investigation among the Machine Learning and Deep Learning algorithms.Before we go any further, Before we go any further, let's take a moment to define some important terms related to machine learning classification and predictive analytic. to classification a few significant terms connected with machine learning classification and prescient investigation.

5.1 Accuracy

Accuracy is the most straightforward. It characterizes absolute number of genuine expectations altogether dataset. It is addressed by the situation of true positive and true negative models partitioned by true positive, false positive, true negative and false negative models.

5.2 Confusion Matrix

This segment portrays the disarray frameworks of all algorithms for dataset. Taking a gander at the disarray framework is a greatly improved procedure to evaluate a classifier's presentation. The fundamental idea is to monitor how frequently instances of class An are ordered as class B. It illuminates clients not just about the shortcomings made by the classifier, yet additionally about the sort of blunders that are being made. Confusion frameworks are utilized to envision significant prescient investigation like review, particularity, precision, and accuracy. Confusion frameworks are helpful in light of the fact that they give direct examinations of values like True Positives, False Positives, True Negatives and False Negatives. Interestingly, other AI characterization measurements like "Exactness" give less valuable data, as Accuracy is essentially the distinction between right expectations partitioned by the complete number of forecasts.

5.3 True/False Positive/Negative

All assessment parameters of the confusion matrix depend on 4 fundamental information sources to be specific True Positive, False Positive, True Negative and False Negative. To comprehend what they are, should check out at a parallel classification problem.

Now that have covered the definitions of key concepts like classification, accuracy, specificity, recall, and precision, we can see how these concepts come together in a confusion matrix. In the realistic underneath, have a dataset with pre-picked marks Positive (light green) and Negative (light red). Since the models in the square region depend on the reality, we refer to it as "The reality." On the other hand, we are attempting to gain proficiency with a characterization model for "The reality" by anticipating the name of "The reality" by means of its highlights. We should characterize "The determination" as our expectations that we foresee them as certain marks, addressed as a circle inside the square. Clearly, the region outside the circle is the predictions which we predict negative names.

True/False is utilized to portray our expectations with "The fact." If a forecast adjusts with the mark it was picked in "The fact," it will be valid, any other way, it will be misleading.

We should investigate region (1) in figure 22. Since this area was positive in "The fact," however we anticipated it negative so we got a misleading expectation. In this manner, it is a False Negative (False means we were erroneous, Negative is from our predictions).

Essentially, region (2) is negative in "also negative in our predictions, which makes it a True Negative. In like manner, region (3) is True Positive and region (4) is False Positive.

Figure 22. : *Basic parameters*

5.3.1 Confusion Matrix of all algorithms

Confusion Matrix of Machine Learning algorithms are shown in below figures (23,24)

Confusion Matrix of Multinomial Naive Bayes are shown below:

Figure 23 showed confusion matrix for Multinomial Naive Bayes algorithm. When i apply this algorithm in my dataset it provided True Prediction value for Negative, Neutral and positive 11764, 2565 and 12185 respectively.A true value is an outcome where the model correctly predicts any class.

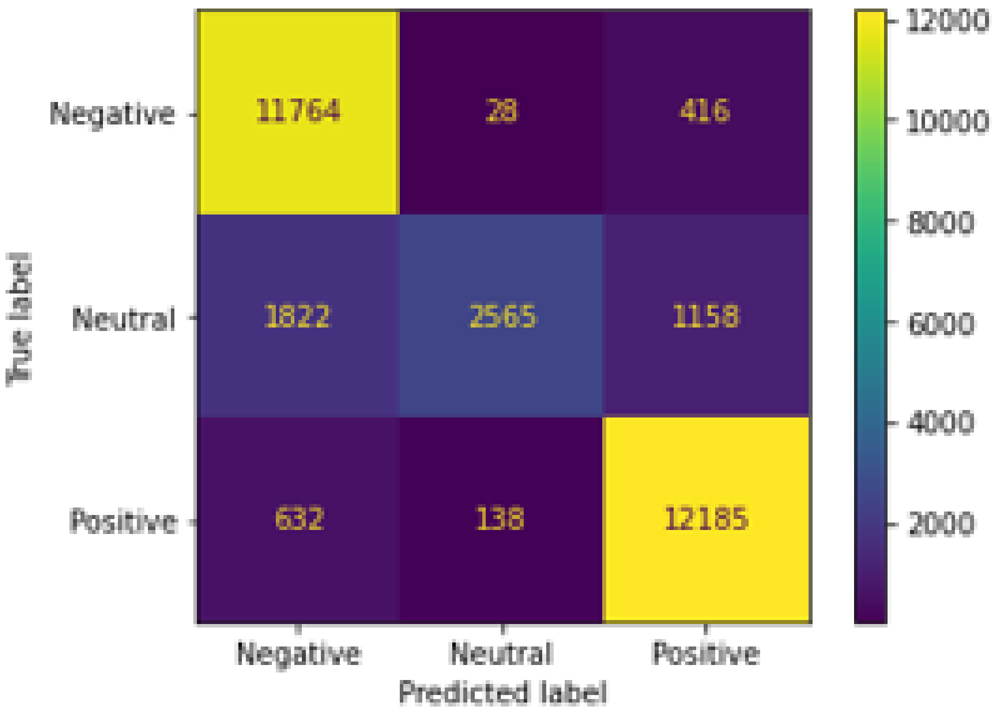


Figure 23. : *Confusion Matrix of Multinomial Naive Bayes*

Confusion Matrix of Multinomial Naive Bayes are shown below:

Figure 24 showed confusion matrix for KNN algorithm. When i apply this algorithm in my dataset it prese nt True value for Negative 8548 , for Neutral 8135 and for positive 11235.A true value is an output where the model correctly predicts any class.

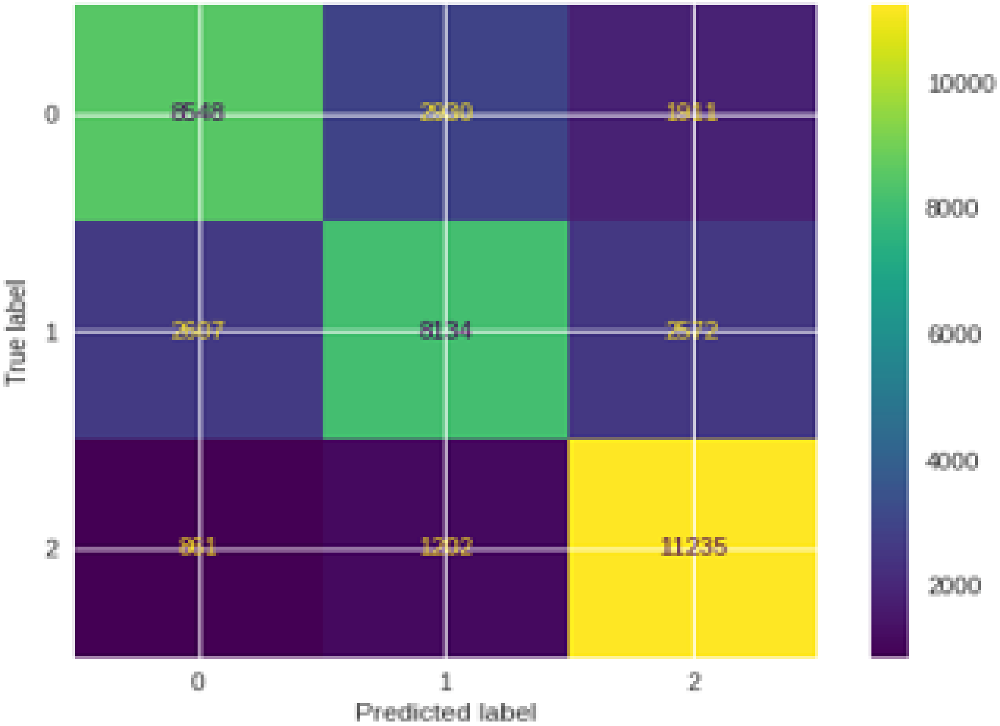


Figure 24. : *Confusion Matrix of KNN*

Comparison analysis among two machine learning algorithm:

Here figure 25 is the chart demonstrations of two machine learning algorithms Multinomial NB and KNN where the confusion matrix is relied upon . Showed that for Multinomial Naive Bayes our dataset gets higher true positive and true negative value.Using KNN our dataset gets only higher value for true neutral. That means for my dataset Multinomial Naive Bayes algorithm works more perfectly than KNN.

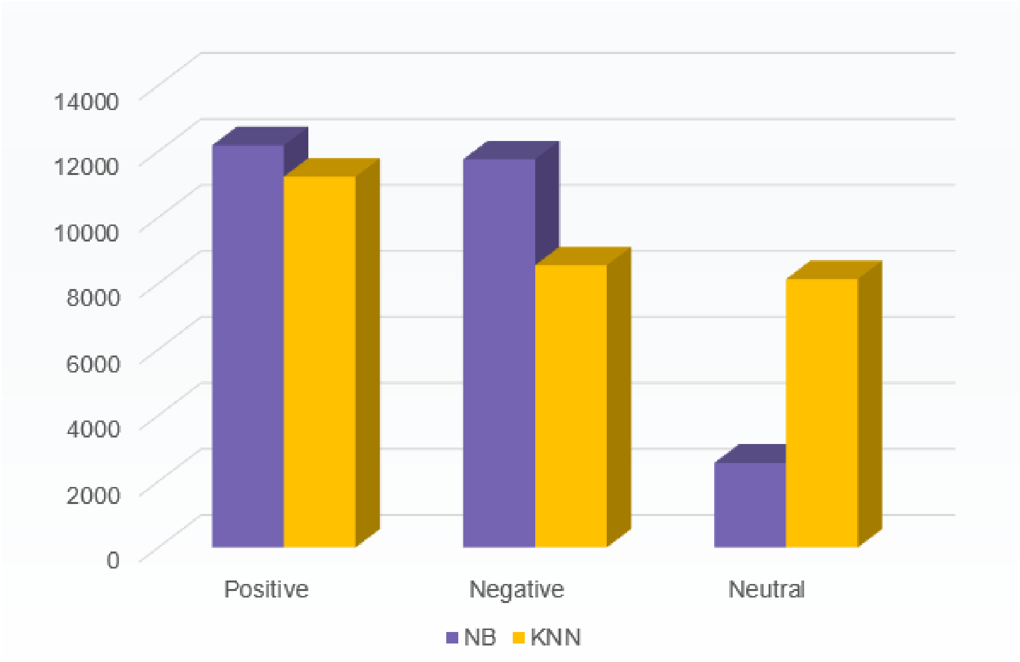


Figure 25. : *Comparison analysis based on true value*

Confusion Matrix of Deep Learning algorithm shown in below figure (23)

Figure 26 showed confusion matrix for LSTM algorithm. When i apply this algorithm in my dataset it present predicted value for Negative 8101 , for Neutral 2765 and for positive 8200.A true value is an output where the model correctly predicts any class.

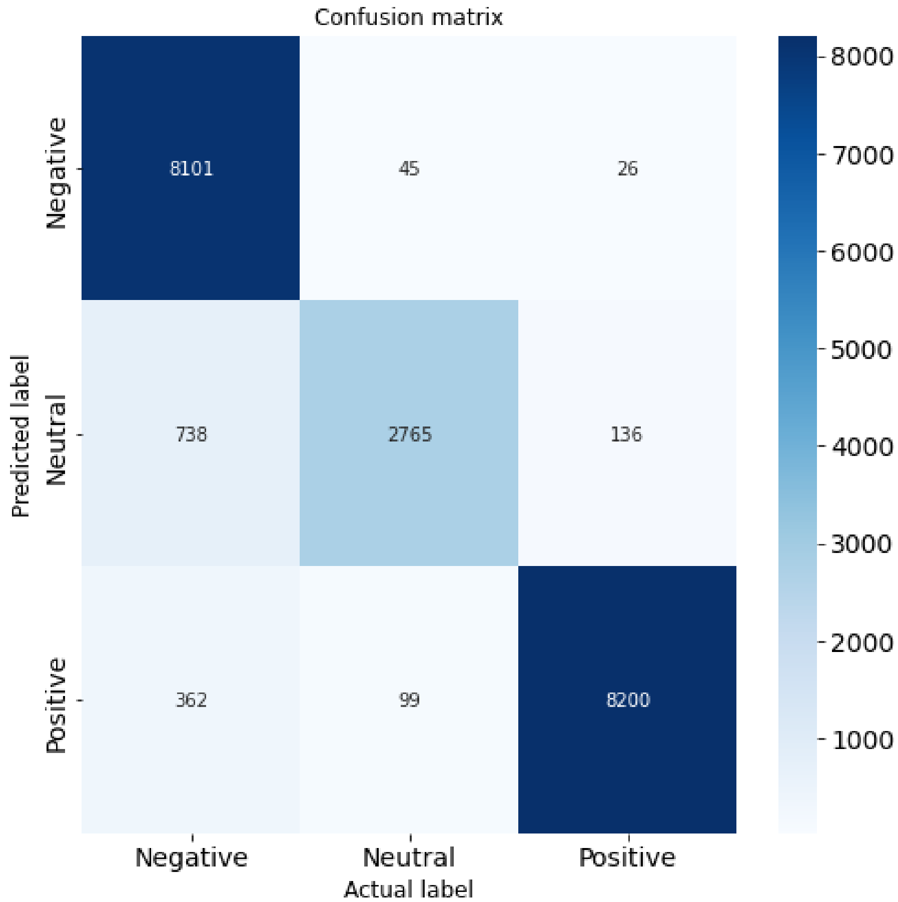


Figure 26. *: Confusion Matrix of LSTM*

5.4 Precision, Recall and F1-scores

Precision: Precision called as positive predictive value which is the fraction of relevant instances among the retrieved instances, It is one sign of a machine learning model's performance – the quality of a positive prediction made by the model. Precision alludes to the number of true positives divided by the total number of positive predictions. Precision is like recall, in the regard that it's worried about your model's expectations of positive models. Be that as it may, accuracy estimates something somewhat unique. Precision is keen on the quantity of really certain models your model distinguished against every one of the models it marked positive. Numerically, it is the quantity of genuine up-sides partitioned by the genuine up-sides in addition to the misleading up-sides.

Recall: Precision called as sensitivity which is the fraction of the total amount of relevant instances that were actually retrieved, It literally implies how many of the true positives were reviewed (found) how many of the correct hits were also found.The term recall alludes to the extent of certifiable positive models that a prescient model has distinguished. To put that another way, it is the quantity of genuine positive models partitioned by the absolute number of positive models and false negatives.

Recall is the level of positive models, from your whole arrangement of positive models, your model had the option to distinguish. Review is likewise some of the time called the hit rate, while responsiveness portrays a model's actual positive expectation rate or the Recall probability.

F1 Score: The F1 score is defined as the harmonic mean between precision and recall. It is used as a statistical measure to rate performance. An F1-score (from 0 to 9, with 0 being the lowest and 9 being the highest) is the mean of an individual's performance, based on two factors, precision and recall.

5.4.1 Precision, Recall and F1-scores of Machine Learning algorithms

For Multinomial Naive Bayes :

	precision	recall	f1-score	support
Negative	0.83	0.96	0.89	12208
Neutral	0.94	0.46	0.62	5545
Positive	0.89	0.94	0.91	12955
accuracy			0.86	30708
macro avg	0.88	0.79	0.81	30708
weighted avg	0.87	0.86	0.85	30708

Figure 27. *: Result summery of Multinomial NB*

For K-Nearest Neighbour :

	precision	recall	f1-score	support
Negative	0.88	0.96	0.92	12208
Neutral	0.82	0.78	0.80	5545
Positive	0.98	0.91	0.94	12955
accuracy			0.91	30708
macro avg	0.89	0.89	0.89	30708
weighted avg	0.91	0.91	0.91	30708

Figure 28. *: Result summery of KNN*

5.4.2 Precision, Recall AND F1-scores of Deep Learning algorithms

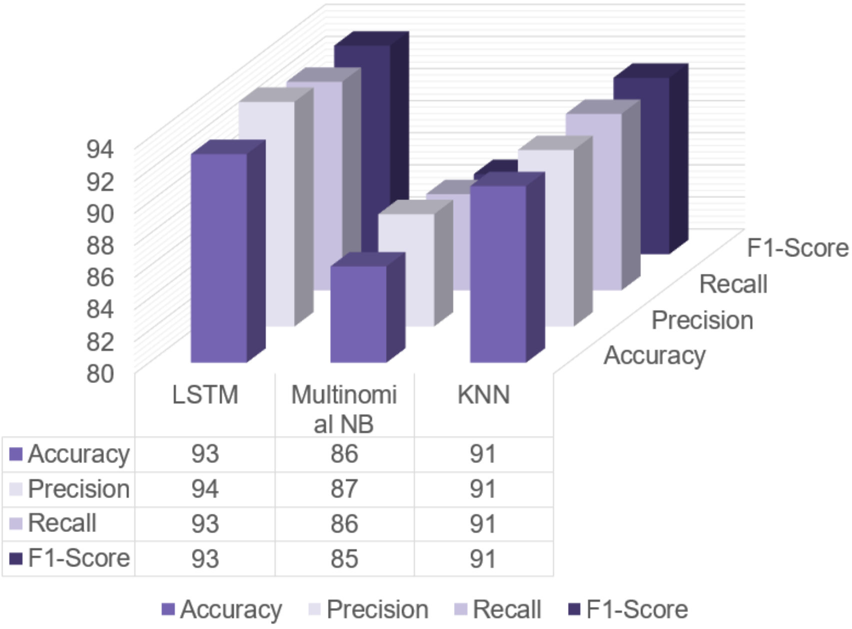
For Long short-term memory :

	precision	recall	f1-score	support
0	0.88	0.99	0.93	8172
1	0.95	0.76	0.84	3639
2	0.98	0.95	0.96	8661
micro avg	0.93	0.93	0.93	20472
macro avg	0.94	0.90	0.91	20472
weighted avg	0.94	0.93	0.93	20472
samples avg	0.93	0.93	0.93	20472

Figure 29. *: Results summery of LSTM*

5.5 Comparison analysis of all machine and deep learning models

For this purpose I have used both machine learning and deep learning models. After using those models I came to know that more accuracy has been found in the deep learning model. Multinomial NB and KNN have been in machine learning less-side LSTM has been used for deep learning



	LSTM	Multinomial NB	KNN
Accuracy	93	86	91
Precision	94	87	91
Recall	93	86	91
F1-Score	93	85	91

Figure 30. : *Result summery of all algorithm*

5.6 ROC curves of all algorithms

The Receiver Operator Characteristic (ROC) curve is an assessment metric for paired classification issues. It is a probability curve that plots the TPR against FPR at different edge values and basically isolates the 'signal' from the 'noise'.

ROC curve of Multinomial Naive Bayes are shown in Figure 28 below

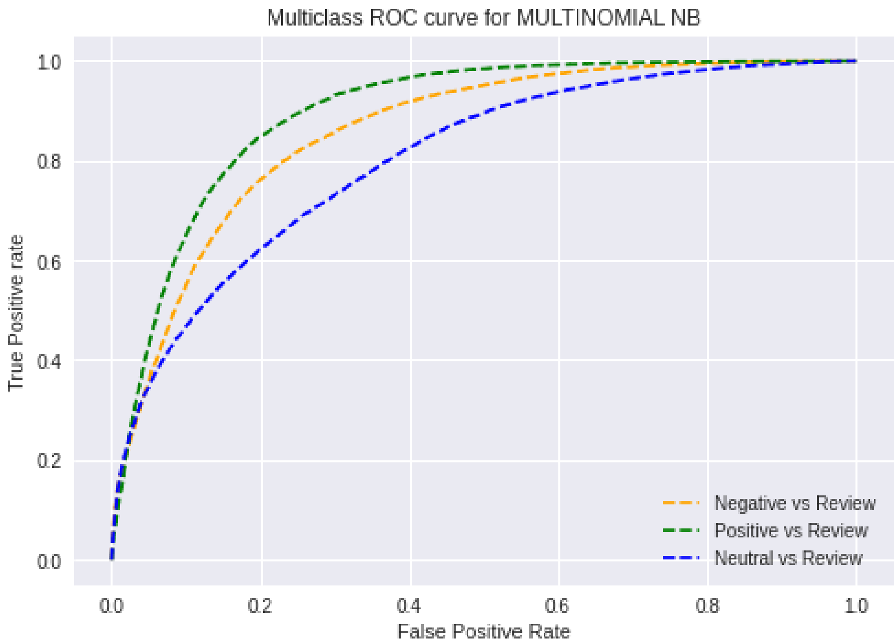


Figure 31. *: ROC curve of Multinomial NB*

ROC curve of KNN are shown in Figure 29 below

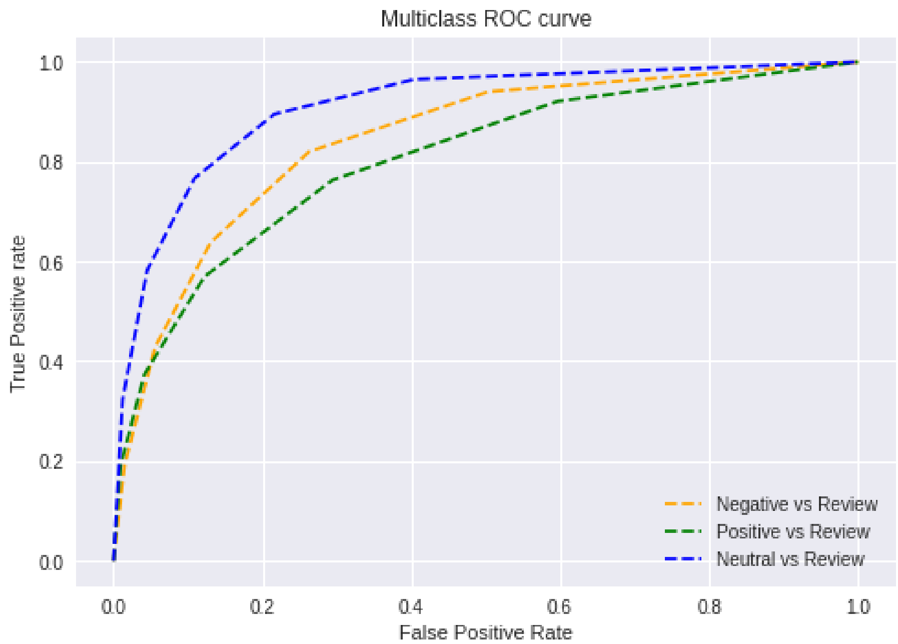


Figure 32. : *ROC curve of KNN*

Loss function curve of LSTM are shown in Figure 30 below

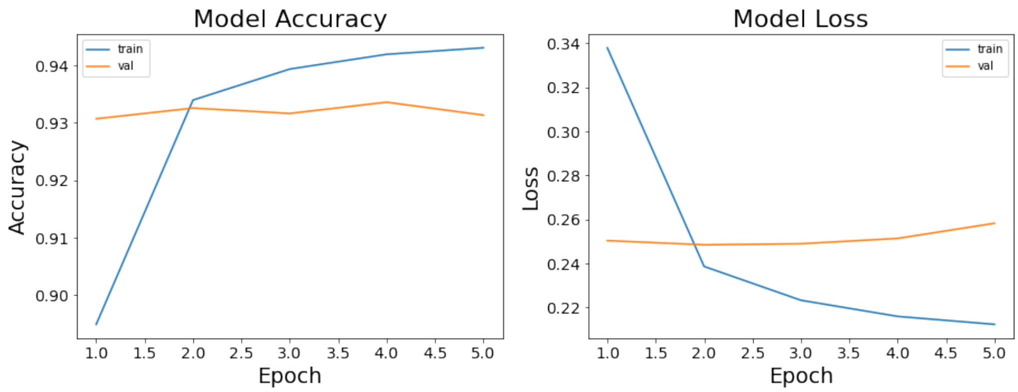


Figure 33. : *Loss Function curve of LSTM*

5.7 Snaps of the predictions made by the final models

Finally the best performing algorithms for each dataset was used for the final detection systems shown in figure below :

At figure 33, the snap shows to test , first a positive sentence is given which gives a positive result.

```
pipe.predict(["Very well..Satisfied better"])
array(['Positive'], dtype=object)
```

Figure 34. : *Prediction of Sentiment text*

Figure 34, though second sentence has a negative but it shows a neutral result. Figure 35 ,

```
pipe.predict(["Most of the time stop working,, while connecting wifi "])
array(['Neutral'], dtype=object)
```

Figure 35. : *Prediction of Sentiment text*

the same thing happens in figure 34 where showed result are not accurate .

```
pipe.predict(["It will be better if i use bkash app from another sim and another phone."])
array(['Positive'], dtype=object)
```

Figure 36. : *Prediction of Sentiment text*

The above testing shows that the model is active and works correctly most of the time to show results

Chapter 6

Conclusion

The goal is to achieve customers satisfaction also reduce costs. The bank company could take some steps for the betterment .This thesis utilized NLP, Machine Learning, and Deep Learning algorithms to distinguish opinion in English language. To direct this exploration, a sum of 101883 texts were gathered. After that every one of the information were cleaned and includes were extricated and the algorithms were prepared. Last execution investigation showed that among all the pre-owned Machine Learning algorithms

6.1 Limitations

Large number of non-English compliment was a limitation to the study.

6.2 Future Work

The future woks of this exploration incorporates, disambiguation of the questionable words present in the dataset, involving all the more enormous corpus and taking into account neighborhood dialects for characterization.

Think that these sentiment could potentially provide interesting insights that can be exploited for future work.

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Appendix

Google Play API

In this thesis, Google play API was used to collected reviews of mobile banking apps .

Code for Scrape :

```
pip install google-play-scrape
from google_play_scraper import app
import pandas as pd
import numpy as np

from google_play_scraper import Sort, reviews_all


us_reviews = reviews_all(
'com.bKash.customerapp',
sleep_milliseconds=0,
lang='en',
country='bn',
sort=Sort.NEWEST,
)
```

```
df_busu = pd.DataFrame(np.array(us_reviews),columns=['review'])
df_busu = df_busu.join(pd.DataFrame(df_busu.pop('review').tolist()))
df_busu.head()
```

6.3 Preprocessing

Remove Punctuation

```
import string
string.punctuation
def remove_punctuation(text):
punctuationfree="".join([i for i in text if i not in string.punctuation]) return punctuationfree
df['clean_review']= df['Reviews'].apply(lambda x:remove_punctuation(str(x)))
```

Lowercase conversion

```
df['clean_review']= df['clean_review'].apply(lambda x: x.lower())
```

Tokenization

```
import re
def tokenization(text):
tokens = re.split('W+',text)
return tokens
df['clean_review']= df['clean_review'].apply(lambda x: tokenization(x))
```

Stop word removal

```
import nltk
nltk.download('stopwords')
stopwords = nltk.corpus.stopwords.words('english')
def remove_stopwords(text):
output= [i for i in text if i not in stopwords]
return output
```

Stemming

```
from nltk.stem.porter import PorterStemmer
porter_stemmer = PorterStemmer()
def stemming(text):
stem_text = [porter_stemmer.stem(word) for word in text]
return stem_text
df['clean_review']=df['clean_review'].apply(lambda x: stemming(x))
```

6.4 Feature Extraction

```
X = df['clean_review']
Y=df['Sentiment']
Z=df['Level']
```

```
X = X.astype(str)
```

```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer(max_features = 1500)
X = cv.fit_transform(X).toarray()
```

6.5 Algorithms Implementation

The following Python code segment demonstrates implementation of Machine Learning and deep learning algorithms.

MULTINOMIAL NB

```
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
nb.fit(X_train_s,y_train_s)
```

KNN

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=20)
knn.fit(X_train,y_train)
predict = knn.predict(X_test)
print(classification_report(y_test,predict))
```

LSTM

def get$_m odel(max_features, embed_dim)$:
$np.random.seed(seed)$
$K.clear_session()$
$model = Sequential()$
$model.add(Embedding(max_features, embed_dim,$
$input_length = X_train.shape[1]))$
$model.add(Conv1D(filters = 32, kernel_size = 3, padding =' same',$
$activation =' relu'))$
$model.add(MaxPooling1D(pool_size = 2))$
$model.add(Conv1D(filters = 32, kernel_size = 3, padding =' same',$
$activation =' relu'))$
$model.add(MaxPooling1D(pool_size = 2))$
$model.add(LSTM(100, dropout = 0.2, recurrent_dropout = 0.2))$
$model.add(Dense(num_classes, activation =' softmax'))$
$model.compile(loss =' categorical_crossentropy', optimizer =' adam',$
$metrics = ['accuracy'])$
$print(model.summary())$
$returnmodel$