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Machine Learning vs Deep Learning Approach for Sentiment Analysis on Twitter Data

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Abstract- *Sentiment Analysis is a process of categorizing whether the text is positive, negative, or neutral. Not only this, but it also includes emotions like happiness, sadness, anger, fear, and surprise. Sentiment analysis can be used in various fields, some well-known fields including online shopping. Sentiment analysis can solve real-time issues and is a crucial task in Natural Language Processing (NLP). We can use traditional Machine Learning algorithms, such as Support Vector Machine (SVM), Tree-based techniques, or Naïve Bayes have been widely used for sentiment analysis. The advent of deep learning (DL) techniques, like CNN, RNN, or state-of-the-art methods, changed this field to capture the more complex patterns in data. This paper presents the comparative study of sentiment analysis using ML and DL techniques. We used ML and DL algorithms against Twitter Sentiment Analysis data and compared the algorithms based on accuracy, computational efficiency, and ability to adopt complex patterns in large datasets. This paper provides insights into the trade-off between ML and DL approaches for Sentiment Analysis, further guiding researchers and practitioners in choosing the appropriate approach for their specific tasks.*

Key Words: Sentiment Analysis, Machine Learning, Deep Learning, RNN, LSTM, GRU

1. INTRODUCTION

As the whole world connects to the internet, data is everywhere, and the famous quote "Data is the new Oil" is relevant to the current world. This data includes customer feedback, reviews on the products they buy, and people's opinions on various topics on different social media platforms. E-commerce websites like Amazon, Flipkart, and Walmart, must analyze the customer's feedback and review the product to increase the product sales. Also, the manufacturer can improve and address the customer's concerns, to enhance the customer's experience and satisfaction by analyzing the sentiment of customers' reviews and feedback. Sentiment analysis can help businesses to monitor their reputation by tracking the comments, and social media reviews. By understanding the user's review, product developer can improve their products. Companies like Twitter, Facebook, and Instagram can analyze people's opinions on current trending topics like elections, and wars to keep the platform safe and make sure that the platform stays neutral for all users and does not get biased in a specific direction. These companies also used sentiment analysis to monitor the tweets and posts to make sure that they are appropriate and follow all the community guidelines, and if someone goes against the guidelines, they remove their content from the platform. We can use Machine Learning and Deep Learning algorithms to classify the sentiment. However, which technique is suitable for problem statements, depends on the data size and ability to adapt to new contexts.

There are a few observations on which the system architecture is proposed.

2. LITERATURE REVIEW

2.1 Lexical or Rule-Based Approach

In "Twitter Sentiment Analysis Using Lexical or Rule-Based Approach: A Case Study" [1], Sheresh Zahoor and Rajesh Rohila use Lexical or Rule Based (unsupervised technique) for Twitter sentiment analysis. Using the Twitter API, they create 4 different datasets. 1. Haryana Assembly Polls 2. ML Khattar 3. The sky is pink (movie) 4. United Nations General Assembly (UNGA). The steps they follow to collect the data and analyze the sentiments are:

1. Data Collection
2. Data pre-processing
3. Part of Speech tagging (POS)
4. Sentiment analysis using an in-built dictionary

A. Data Collection:
To collect data from Twitter, they use the Twitter API, collect the tweet, and save it in CSV format. The CSV file contains the date, text, retweet, hashtag, and followers.

B. Data Pre-Processing:
To prepare data for sentiment analysis, they perform various operations on data, including tokenization or Bag-of-words, N-gram Extraction, Stemming and Lemmatization, and StopWords removal.

C. Part-of-Speech (POS):
Process of automatically tagging each word by their grammatical feature, such as Noun, Pronoun, verb, adverb, etc.

D. Model Evaluation:
They used TextBlob and VADER built-in libraries available in Python. TextBlob is an open-source NLTK-based library, whereas VADER (Valence Aware Dictionary and Sentiment Reasoner) is used for lexicon-based sentiment analysis. The result they conclude is:

Sentiment	Haryana Assembly Polls		ML Khattar	
	Text Blob	VADER	Text Blob	VADER
Positive	29.7%	44%	58.5%	58.5%
Negative	12.0%	17.6%	9.6%	9.6%
Neutral	58.3%	38.5%	32%	20.5%

Sentiment	The sky is pink		UNGA	
	Text Blob	VADER	Text Blob	VADER
Positive	64.1%	62.8%	36.2%	33.4%
Negative	12.1%	12.7%	12.6%	40.1%
Neutral	23.8%	24.5%	251.2%	26.5%

The conclusion of this case study found that the results obtained from unsupervised techniques are not accurate and subject to change.

2.2 Deep Learning Approach

Vasily D. Derbentsev and Vitalii S. Bezkorovainyi et al. published "A Comparative Study of Deep Learning Models for Sentiment Analysis of Social Media Texts" [2] paper. The author of this paper presents a comparative study of a deep learning model for sentiment analysis of social media text. They used Deep Neural Network (DNN), Convolutional Neural Network (CNN), Long-Short Term Memory (LSTM) architecture, and Logistic Regression classifier as a baseline. They chose 2 datasets for their study: one is IMDB Movie Reviews, and the other is Twitter Sentiment 140.

For Feature Extraction, they follow Bag of Words (BOW), N-grams, TF-IDF, word embedding

A. Pre-processing and word embeddings

For the text-preprocessing task, they used the NLKT library, and this task includes removing punctuations, markup tags, HTML, and Tweet addresses, removing stopwords, and converting all words into lowercase words.

B. DNN models design and hyperparameter settings

1. Used pre-trained GloVe embeddings of size 100 in the first layer (embedding layer).
2. First model CNN with three convolutional layers with different kernel sizes and used Maxpooling layers between them and then flatten and Dense layer.
3. In the second approach, they combine the CNN+LSTM.
4. Third, CNN + BiLSTM (forward and Backward LSTM).
5. To obstruct overfitting, Dropout layers are used.

C. Evaluation:

IMDB Dataset

Models	LR	CNN	CNN-LSTM	CNN-BiLSTM
Precision	86.62%	90.04%	90.90%	83.08%
Recall	85.54%	90.31%	84.84%	93.25%
F1-Score	86.08%	90.18%	87.76%	87.87%
Accuracy	85.90%	90.09%	88.08%	87.03%

Twitter-140 dataset

Models	LR	CNN	CNN-LSTM	CNN-BiLSTM
Precision	71.61%	76.17%	78.98%	79.54%
Recall	74.63%	79.47%	77.47%	84.41%
F1-Score	73.09%	77.78%	78.23%	81.91%
Accuracy	79.54%	77.24%	78.37%	82.10%

The experiment showed that LR (baseline) achieved 85.9% (74.23%), CNN achieved 90.09% (77.24%), CNN-LSTM reached 88.01% (78.36%), and BiLSTM-CNN attained 87.03% (82.10%).

2.3 Machine Learning Algorithms

In "Sentiment Analysis of Twitter Data: A Survey of Techniques" [3], the paper's authors, Vishal and S. Sonawane, use machine learning algorithms on a comparatively small dataset publicly made available by Stanford University. They studied Naïve Bayes, Max Entropy, and Support Vector Machine algorithms. Also, they compared the result with the various data pre-processing techniques like stopwords removal, Unigram, and Trigram.

A. Data Processing

StopWords: Words like I, am, you, your, etc. are removed during the data processing step because these words do not add much information to the text for sentiment analysis.

Bigram: It uses a combination of two words, e.g., "Not happy" clearly indicating the negative sentiment.

B. Evaluation

1. They achieve 73.56% accuracy without using StopWords removal, Unigram, and Bigram techniques.

2. Naïve Bayes Algorithm

Algorithm	Accuracy
Naïve Bayes (Unigram)	74.56%
Naïve Bayes (Bigram)	76.44%
Naïve Bayes (trigram)	75.41%

3. Support Vector Machine (SVM)

Algorithm	Accuracy
SVM with unigram	76.68%
SVM with bigram	77.73%

The paper concludes that the Support Vector Machine and Naïve Bayes algorithms give the highest accuracy, and in some cases, lexicon-based methods are effective.

3. SYSTEM ARCHITECTURE

Dataset

We used the Sentiment140[4] dataset for our experiment. The dataset contains 1.6 million tweets. The dataset has a target, ids, date, flag, user, and text columns.

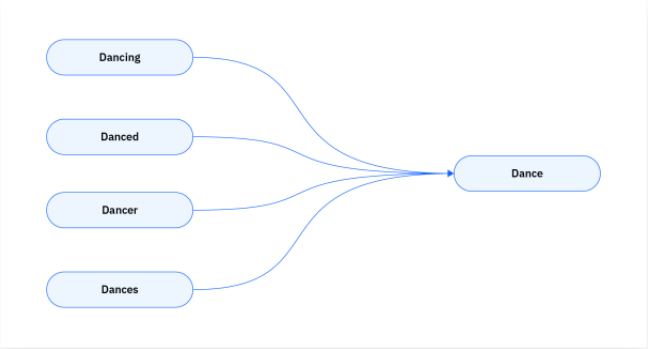
i. Target: the polarity of tweets (0: Negative, 4: Positive)
ii. Ids: id of the tweet
iii. Date: date of the tweet
iv. Flag: query
v. User: The user who tweeted
vi. Text: text of the tweet.

The dataset has **0.8M positive** and **0.8M negative** tweets.

DATA PROCESSING

This dataset has no column names, so we manually give names to each column for our better understanding to make the process easy to understand the data. The column names are target, ids, date, flag, user, and text. We then checked if any column contained any null values or not and found that there were no null values present in any of the columns. The dataset has an equal number of Positive and negative Tweets i.e.,0.8M tweets in each category. For the target column, 0 represents Negative sentiment and 4 represents Positive sentiment. We replaced 4 with 1, as it gives more context to the data. We apply the following data pre-processing and data cleaning operations to data.

1. StopWords Remove: Use the NLTK library to remove all the stopwords from the data, as these words do not contribute much to prediction.
2. Removal of Special characters and converting all words to a lowercase word: To remove any special characters such as @, //, etc. from the data, we use a regular expression library to find these characters and remove them. We convert all words into lowercase words.
3. Stemming: In natural language processing (NLP), stemming is a text-preprocessing method. In particular, it is the act of condensing a word's inflected form into a single "stem," or basic form—also referred to as a "lemma" in linguistics.



We used the PortStemmer function from the NLTK library to perform the stemming operation. Then we add the “stemmed_text” newly created column to our dataset after performing the stemming step.

(The above operation is performed on “text” columns)

FEATURE EXTRACTION

After data processing, we extract only the “target” and the newly added “stemmed_text” column for further processing. All other columns are not required for sentiment analysis. After this, the next step is to split the data into train-test splits. For this, we used scikit-learn train_test_split functions with the splitting ratio of 80:20, i.e., 80% data for training purposes and 20% data for testing purposes. To convert the text into vectors, we used the TF-IDF technique.

TF-IDF: Term Frequency Inverse Document Frequency (TF-IDF) is an algorithm to transfer text into a meaningful representation of numbers (vectors)

1. Term Frequency (TF):
To measure how frequently a word (term) appears in text.

$$\mathrm{TF}(t, d) = \frac{\text{count of t in d}}{\text{number of words in d}}$$

2. Inverse Document Frequency (IDF):
It measures how important a word is with entire text corpus.

$$\mathrm{IDF} = \mathrm{Log}\left(\frac{\text{Total no of documetns in corpus D}}{\text{No. of documents containig term t}}\right)$$

3. TF-IDF Score:

$$TF - IDF(t, f, D) = TF(t, d) \times IDF(t, D)$$

3.1 MODEL TRAINING AND RESULT

Machine Learning Algorithms

1. Logistic Regression

For classification issues, supervised machine learning algorithms like logistic regression are employed. It is a statistical algorithm. It is a statistical algorithm. For predicting the output, it uses Sigmoid functions, which take inputs and produce probability values between 0 and 1.

Sigmoid Function:

$$z = w.X + b$$

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

2. NAÏVE BAYES

Based on Baye's theorem, the Naïve Bayes algorithm is used for classification. The algorithm's presumptions are indicated by the label "Naïve." The algorithm assumes that features(columns) are independent of each other.

Bayes Theorem:

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

Where, y=Class Labels and X= dependent features(columns)

3. XGBOOST CLASSIFIER

Extreme Gradient Boosting (XGBoost) is an ensemble learning method that combines predictions of multiple weak models to produce a stronger prediction (weaker → stronger). It is widely used because it can handle a large dataset and handling of missing values without requiring significant pre-processing. It is an implementation of the Gradient Boosted Decision Tree.

Deep Learning Architecture:

1. RNN ARCHITECTURE

RNNs are used for tasks that involve sequential data, such as time series prediction, natural language processing (NLP), and speech recognition.

RNNs are like networks that have a memory. They process data one step at a time and remember information from previous steps. Imagine reading a sentence word by word. An RNN processes each word in order and keeps track of the context from previous words to understand the sentence better. This memory aspect helps RNNs make decisions based on the sequence of data, such as predicting the next word in a sentence or recognizing spoken words over time. RNNs are very similar to feedforward neural networks, except is also have a connection pointing backward.

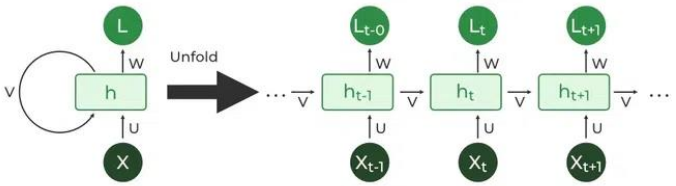


Fig 1.1 – RNN Network

Because of unstable gradients, RNN suffers from two major problems: 1) Problem of long-term dependency and (Vanishing gradient problem) 2) Stagnated Training (Exploding gradient problem).

As sequence length increases, RNN struggles to remember the initial time-step context, and this issue arises because of the vanishing gradient problem, and because of the exploding gradient, the stagnated training problem occurs.

2. LSTM AND BiLSTM ARCHITECTURE

To tackle the Long-Term dependency problem, Sepp Hochreiter and Jurgen Schmihuber introduced the "Long-Short-Term Memory (LSTM)" [5] architecture.

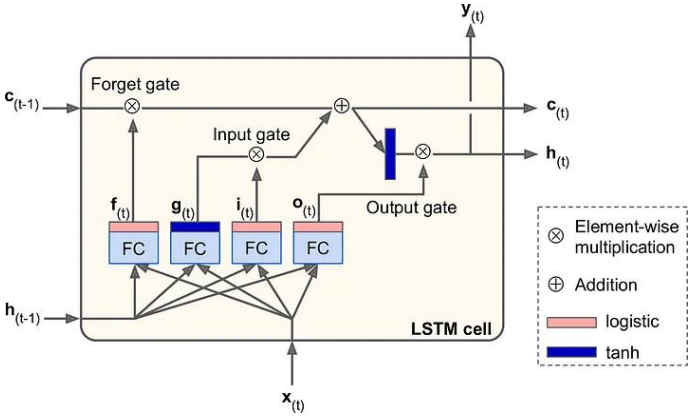


Fig 2.1 - LSTM Cell

From $c_{(t-1)}$ to $c_{(t)}$ the LSTM cell decides which part has to remove (forget) and what to add based on input ($x_{(t)}$)

LSTM Cell has two states:

1. $c_{(t)}$ (Cell state) → Long Term State, for remembering information for a longer duration
2. $h_{(t)}$ (Hidden state) → Short Term State, for remembering information for short durations

The key idea behind these two states is what to keep and what to discard.

Type of gates in LSTM:

1. Forget gate ($f_{(t)}$): It determines which elements of the permanent state should be removed.
2. Input gate ($i_{(t)}$): it controls which parts of $g(y_t)$ should be added to long-term state.
3. Output gate($o_{(t)}$): it controls which part of the long-term state should be read and output at this time step, both to h(t) and $y_{(t)}$.

LSTM computations:

$$i_{(t)} = \sigma(W_{xi}^T X_{(t)} + W_{hi}^T h_{(t-1)} + b_i)$$

$$f_{(t)} = \sigma(W_{xf}^T X_{(t)} + W_{hf}^T h_{(t-1)} + b_f)$$

$$o_{(t)} = \sigma(W_{xo}^T X_{(t)} + W_{ho}^T h_{(t-1)} + b_o)$$

$$g_{(t)} = \tanh(W_{xg}^T X_{(t)} + W_{hg}^T h_{(t-1)} + b_g)$$

$$c_{(t)} = \sigma(f_{(t)} \otimes c_{(t-1)} + i_{(t)} \otimes g_{(t)})$$

$$y_{(t)} = h_{(t)} = o_{(t)} \otimes \tanh(c_{(t)})$$

Here,

w_{xi}, w_{xf}, w_{xo}, and w_{xg} are the weight matrices of each of the four layers for their connections to the input vector $x_{(t)}$.
w_{hi}, w_{hf} ,w_{ho}, and w_{hg} are the weight matrices of each of the four layers for their connection to the previous short-term state $h_{(t-1)}$.
b_i, b_f, b_o, and b_g are the biases for each of the four layers.

BiLSTM

To improve the performance of LSTM, the BiLSTM architecture is introduced, which captures the dependencies in both forward and backward directions of sequence. It uses two LSTM layers:

1. Forward LSTM: It processed the sequence from left to right (Start to End) direction.
2. Backward LSTM: It processes the sequence from right to left (end to start)

Then, output from both LSTMs is combined, which allows the model to consider the context from both directions at each time step.

3. GRU ARCHITECTURE

The Gated Recurrent Unit (GRU) cell was proposed by Kyunghyun Cho et al. in a 2014 paper titled "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation." [6]

GRU is a reduced version of the LSTM cell, and it claims to achieve similar results to LSTM. The simplifications are:

1. A single vector $h_{(t)}$ is a combination of both state vectors.
2. A single gate controller $x_{(t)}$ controls the forget gate and input gate.
3. Full state vector $h_{(t)}$ is the output of every time step $h_{(t)}=y_{(t)}$
4. New gate controller $r_{(t)}$ that controls which part of the previous state will be shown to the layer $g_{(t)}$.

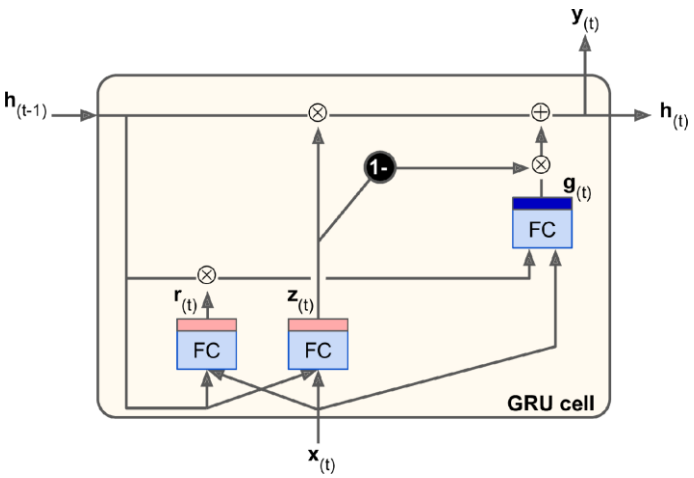


Fig 4.1 GRU Cell

GRU Computations

$$z_{(t)} = \sigma(W_{xz}^T X_{(t)} + W_{hz}^T h_{(t-1)} + b_z)$$

$$r_{(t)} = \sigma(W_{xr}^T X_{(t)} + W_{hr}^T h_{(t-1)} + b_r)$$

$$g_{(t)} = \tanh(W_{xg}^T X_{(t)} + W_{hg}^T (r_t \otimes h_{(t-1)}) + b_g)$$

$$h_{(t)} = z_{(t)} \otimes h_{(t-1)} + (1 - z_{(t)}) \otimes g_{(t)})$$

3.2 TRAINING AND RESULT

Machine Learning Algorithms

We used Logistic Regression (LR) as a baseline model to compare the accuracy of the other models.

Models	LR	MNB	XGBoost
Precision	75.62%	**75.28%**	75.62%
Recall	**78.96%**	75.12%	**78.96%**
F1-Score	77.25%	75.2%	77.25%
Accuracy	76.75%	75.23%	76.75%

Deep Learning Algorithms

For each architecture, we used the Adam optimizer with a learning rate of 0.001, the sigmoid activation function for the output (last) layer, binary cross-entropy as the loss function, accuracy as the metric, 50 epochs, and a batch size of 128.

For the LSTM, BiLSTM, and GRU architectures, we used the ReLU activation function in the Dense layer and to avoid overfitting, we applied L2 regularization.

Model Summary

Models	Layers	Parameters
Simple RNN	Embedding	input_dim=5000, output_dim=100, input_length=50
	simpleRNN	128, return_sequence=True
	Dropout	0.5
	simpleRNN	64, return_sequence=True
	Dropout	0.5
	simpleRNN	32
	dense	1, activation=" Sigmoid"
LSTM	Embedding	input_dim=5000, output_dim=100, input_length=50
	LSTM	128, return_sequence=True kernel_regularizer=l2(0.001)
	Dropout	0.4
	LSTM	64
	Dropout	0.4
	Dense	64, activation='relu', kernel_regularizer=l2(0.001)
	dropout	0.4
	dense	1, activation='sigmoid'
BiLSTM	Embedding	input_dim=5000, output_dim=100, input_length=50
	Bidirectional (LSTM)	128, return_sequence=True kernel_regularizer=l2(0.001)
	Dropout	0.4
	Bidirectional (LSTM)	64
	Dropout	0.4
	Dense	64, activation='relu', kernel_regularizer=l2(0.001)
	dropout	0.4
	dense	1, activation='sigmoid'
GRU	Embedding	input_dim=5000, output_dim=100, input_length=50
	Bidirectional (LSTM)	128, return_sequence=True kernel_regularizer=l2(0.001)
	Dropout	0.4
	Bidirectional (LSTM)	64
	Dropout	0.4
	Dense	64, activation='relu', kernel_regularizer=l2(0.001)
	dropout	0.4
	dense	1, activation='sigmoid'

RESULT

Models	RNN	LSTM	BiLSTM	GRU
Precision	76.47%	77.41%	76.52%	77.84%
Recall	75.75%	**78.27%**	**77.96%**	**78.01%**
F1-Score	**77.6%**	77.84%	77.55%	77.92%
Accuracy	77.19%	77.64%	77.5%	77.83

4. CONCLUSION

In this paper, we apply both machine learning and deep learning techniques to the sentiment140 dataset. This large dataset (1.6M tweets) is best for comparing the ML and DL algorithms. We found that the machine learning algorithm achieved a maximum of 76.75% accuracy, whereas with only 50 epochs we crossed 77% accuracy with a simple RNN model with a limited number of parameters, and with LSTM we crossed 82% training accuracy. Hence, we can conclude that deep learning architecture outperforms machine learning techniques. As with limited resources, we are not able to do much experimentation. For future studies, we plan to increase the epoch size, increase the LSTM and GRU layers, and compare the results.

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