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Full Length Research Paper

COVID-19 Impact on UK Unemployment Rate: A Social Media Sentiment Analysis

Kelly Ochuko Egode

MSc Artificial Intelligence and Data Science, University of Hull, UK,

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The COVID-19 pandemic has left its mark across every facet of our life today. Its consequences on unemployment due to restrictions on social interaction among people, economic collapse, and fear of business continuity led people to express their concerns on social media. The Twitter platform had been a source of unstructured data for different COVID-19 analysis. In this work, we have analysed 197,669 tweets by country and cities to utilise sentiment analysis. A natural language processing (NLP) technique for opinion mining to extract neutral, positive and negative sentiments on COVID-19; and its impact on the unemployment rate in the United Kingdom. We investigated deep learning techniques with Long-Short Term Memory networks (LSTMs) and Bidirectional Long-Short Term Memory networks (Bi-LSTM), on Twitter data during the pandemic lockdown, March 2020 and September 2021 after the furlough is closed. Using Bi-LSTM, which gives 91% accuracy and 87% F1-score, precision and recall each. Our study shows that the lockdown witnessed a positive sentiment between March – May 2020 and greater number of negative tweets in the United Kingdom during the peak unemployment rate of June – October, 2020. England and Scotland had similar trends, together with their largest cities London and Glasgow respectively. Furthermore, we observed a significant reduction in negative sentiments tweet responses from 3.67% in July 2020 to 0.83% in May 2021; while the unemployment rate is at its peak. This is attributed to the period the second phase of Coronavirus Job Retention Scheme (CJRS) known as flexible furlough was introduced.

Keywords: COVID-19, UK unemployment rate and social media.

INTRODUCTION AND BACKGROUND

A study on COVID-19 pandemic and social media revealed there are over 2.11Bn COVID-19 tweets in the Twitter microblogging platform (Lamsal, 2020), a source of unstructured big data to mine public sentiments on various topics related to the novel coronavirus (WHO, 2020).

There were several initiatives to slow the COVID-19 pandemic's rapid spread, policies were put in place, and by the first quarter of 2020, entire spheres of the UK economic and social life had either been completely shut down or had undergone significant restrictions (Houston,

2020). There has been drastic limitation on public transportation, air travel has been suspended, and restaurants, stores, and recreational facilities have been ordered to close (Joyce and Xu, 2020). Thus, cases of unemployment had suddenly been experienced as companies sacked their staff due to inability to pay salaries.

Thus, the Coronavirus Job Retention Scheme (CJRS) was established by the UK government to address unemployment among persons who were available for

work during the pandemic (UK Parliament, 2022), CJRS withdrawal on September 30, 2021 recorded 1.2 million jobs still in furlough on that day. The UK unemployment rate increased from 4.4% in mid-2020 to 5.3% in December 2020 (Office for National Statistics, 2022).

The COVID-19 pandemic is still among the most critical global threats. Understanding human emotions during pandemics has been researched, our focus is using machine and deep learning models for sentiment analysis.

(Jabbar and Shahzad, 2022) examined how the pandemic had impacted the trend on global employment. The COVID-19 pandemic's peak or low employment of different countries in America, Asia, Europe and Africa were classified using VADER algorithm sentiment analysis on the COVID-19 cases trend. They noted that between May – July 2020 sentiments towards employment were very low while COVID-19 cases were increasing. On the other hand, between September – November 2020, the cases were very high. However, the sentiments towards the employment issues were on an increase towards positive. These trends, they attributed to initial shock of impact of covid-19 and its subsequent sack of employees worldwide. Then, people were more aware of living with the pandemic; subsequently, more people were re-employed as organisations opened.

Furthermore, (Chandra and Krishna, 2021) developed an LSTM and BERT multi-label framework and investigated the hypothesis of more than one emotion being expressed at once. The models used GloVe embedding of 300 dimensions on the Senwave COVID-19 dataset. They were able to obtain monthly sentiments expressed in Maharastra and Delhi, India during the 2020 COVID-19 pandemic. The findings of the multi-label sentiment classification revealed a significant amount of optimistic positive tweets, with the highest emotions being optimistic, annoyed, and joking, and a small number of negative sentiments expressed. In addition, they obtained LSTM, Bi-LSTM and BERTF1 micro metrics of 0.493, 0.495 and 0.534 respectively.

In another experiment on sentiment polarity and emotion classification of neighbouring countries during the COVID-19, LSTM assessment multi-layer model was used on sentiment140 dataset. The retrieved tweets and emoticons attained state-of-the-art training and validation accuracy of 96% and 83% respectively; on tweet polarity emanating from the United States and Canada, as well as Pakistan and India. However, irrespective of the cultural commonalities, Sweden and Norway displayed an opposite polarity trend (Imran et al., 2020a). (Nirmala et al., 2015) used sentiment analysis scores of tweets to establish a significant link between public expressions and bad feelings; to reveal the unemployment rate.

In another study of the effect of COVID-19 on the UK adults' mental health (Chandola et al., 2020) emphasised unemployment as a stressor element. Thus, more people lost their jobs with less income and savings (Dang and Viet

Nguyen, 2021).

Other studies have applied sentiment analysis and deep learning natural language processing techniques to classify people's attitudes, sentiments subjectivity, polarity, affect, sarcasm, opinions and emotions from tweets, documents, images, audios and videos (Cortis and Davis, 2020; Yadav and Vishwakarma, 2020; Yue et al., 2019). Thus, in this study, we specifically address the impact of COVID-19 on UK unemployment rate by determining the optimal deep learning model.

DATA AND METHODOLOGY

Data and Data collection

The dataset (TrackMyHashTag, 2022) is COVID-19 tweets obtained during UK shutdown period of March 1, 2020 to end of Furlough September 30, 2021 with predefined search hashtags (Dey et al., 2020) "CORONA", "unemployment", "workfromhome", "lockdown" and "furlough". The dataset was labelled by the vendor, however there is strong imbalance in the number of negatives compared to the neutral and positive sentiments. Thus, VADER and TEXTBlob were further used to automatically label the dataset. We observed similar imbalance trend. Then, F-one-way ANOVA hypothesis was performed to see if the mean distributions of each sentiment differed from one another statistically. We obtained probability of statistically significantly different distributions, and accepted the alternative hypothesis. This result is same for the three label types.

In addition, the column 'Tweet Posted Time' was used to produce 'Year' and 'Year_Month' columns. Also, the Location column was used to produce 'Tweet Country' and 'Tweet City'.

Methodology

We used deep learning-based language models such as Valence Aware Dictionary and sEntiment Reasoner (VADER)(Hutto and Gilbert, 2014); TEXTBlob (Steven L, 2020); Global Vectors for Word Representation (GloVe)(Pennington et al., 2014); Long Short-Term Memory (LSTM) (S. Hochreiter and J. Schmidhuber, 1997); and Bidirectional Long Short-Term Memory (Bi-LSTM) (Schuster and Paliwal, 1997).

The COVID-19 dataset is labelled by the vendor TrackMyHashTag. However, VADER and TEXTBlob were further used to automatically classify tweets sentiments (Figure 1). Thereafter, a supervised machine learning algorithm, Naïve Bayes classifier (Pedregosa et al., 2011) was used to determine the sentiment classification of the tweets baseline. The Naïve Bayes algorithm is very efficient and effective in inductive learning methods and performance. The LSTM and Bi-LSTM models with GloVe

Figure 1. WordCloud showing the most frequent words expressed in the dataset.

Sentiment Analysis Model

To enable the model to use the data for effective prediction, data collection, pre-processing, analysis, and feature engineering are required. As a result, Naïve Bayes would require cleaning, but the other deep learning models would not.

GloVe Word Embedding

Global Vectors for Word Representation (GloVe) is an unsupervised learning algorithm. It is pre-trained word embeddings / vector technique of global and local word-word co-occurrence statistics from a corpus (Pennington et al., 2014); to infer the link between words. It provides a word vector representation of a principal loss function

VADER Model

Valence Aware Dictionary and sEntiment Reasoner (VADER) is a pre-trained rule-based sentiment lexicon that is specific to social media dataset. This model was used to label the dataset because of its sensitivity to the polarity and intensity of the emotions expressed in the tweets (Chandrasekaran et al., 2020). Its sentiment score consists of neutral, positive, negative and compound; which is based on the sum of values of the preceding three and is impacted by punctuation, capitalization and emoji (Crocamo et al., 2021).

TEXTBlob Model

TEXTBlob is an NLTK text processing package for Python. It offers a unified API for Part-of-Speech, PoS tagging, noun phrase extraction, sentiment analysis, and other standard natural language processing (NLP) activities (Steven L, 2020). This model was used to label the tweets' emotion subjectivity or objectivity level and ranked the tweets sentiment polarity [-1.0,1.0] and subjectivity [0.0,1.0] (Nawaz Ali and Md et al., 2021).

Naïve Bayes Model

This is a statistical technique based on Bayes theorem and independent feature assumption. The tweets in words and sentences are translated into numbers (Rustam et al., 2021a). The Multinomial Naïve Bayes model was used; its input are the translated data to perform sentiment analysis on tweets. The hyper-tuned model was used to establish a baseline for the framework. The probability inferences, P on the target class, y and independent variable tweets, X were obtained based on the mathematical expression shown in equation 1.

$$P(X) = \frac{P(y)*P(y)}{P(X)}, \quad (1)$$

LSTM Model

The Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) (S. Hochreiter and J. Schmidhuber, 1997); deep learning model that was created to overcome the problem of gradient disappearance in RNNs owing to backpropagation (Jelodar et al., 2020; Staudemeyer and Morris, 2019). The cell states of LSTM which are controlled by the three gates (input, forget and output) helps resolve the RNN (Chuluunsaikhan et al., 2020). It uses the hidden state process of carrying memory forward as expressed mathematically in equation 2.

$$h_t = \phi(Wx_t + Uh_{t-1}), \quad (2)$$

Where h_t is hidden state at time t . W is the weight matrix, and U is the transition matrix. ϕ is the activation function (Imran et al., 2020b).

Bi-directional LSTM Model

Bi-LSTM requires an additional LSTM to ensure the sequence of weighted word vectors (Zhang et al., 2015) are input in two directions; backward or forward to capture the context information effectively (Xu et al., 2019). The Bi-LSTM model sentiment classification will also get its input as the GloVe embedding performed on tweets (Kamyab et al., 2021).

Experiments

To enable effective pre-processing of the tweets, various user-defined functions were implemented. Then tokenization, lemmatization, WordCloud, N-grams and hashtags were generated to get better insights and understanding of the sentiments.

For the machine learning Naïve Bayes model, using the SKlearn `train_test_split` function; I splitted the dataset into 80:20 ratio for training and testing. I then vectorized the input data using the Term Frequency Inverse Document Frequency, TF-IDF. Thereafter, sentiment analysis was carried out on the training and testing data using Naïve Bayes algorithm with $\alpha = 0.01$. The 80:20 ratio was compared to another split ratio of 90:10 and arrived at similar validation results. The imbalanced target label dataset was resampled using SKlearn Imblearn library – SMOTE (Synthetic Minority Oversampling Technique) and NEARMISS undersampling to get a balanced target label dataset.

The Deep learning methods entails LSTM and Bi_LSTM using GloVe embedding Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 100d vectors), TensorFlow Keras framework with activation functions - Rectified Linear Unit (ReLU) and Hyperbolic Tangent (Tanh) used at dense layers and softmax at the output layer, optimizer - Adaptive Moment Estimation (Adams) and loss function is categorical crossentropy because of the multi class dataset. The different architectures in Table 1b were trained on the deep learning models. Thereafter, KerasTuner hyper parameter tuning was used to tune the two models and their optimal architecture retrained (Rustam et al., 2021b). The imbalanced target label was addressed using the keras class weights.

One of the objectives of the project is to evaluate the classification optimal performance on the sentiments on unemployment during the pandemic. The optimal model was selected from among the models based on their performance and measurement evaluation using Classification Accuracy metrics: a fraction of predictions the model got correctly; Balanced Accuracy metric – due to the unbalanced label target; Confusion Matrix: a basis for baseline evaluation for other models that shows summary table of number text tweets correctly and incorrectly classified; Precision: identify the correctness of classification; Recall: shows the number of positive sentiments correctly identified out of the total number of

positive tweets; F1-score/measure: balances precision and recall; and AUC-ROC: Area under Receiver operating characteristics that balances true positive and the false-positive rates for our model. More emphasis is on the F1 - score and AUC score due to the imbalanced target dataset.

The Office for National Statistics, ONS monthly unemployment rate for United Kingdom, England, Scotland, Wales and Northern Ireland were downloaded from the website (ONS, 2022). The unemployment rate data and the sentiments expressed due to COVID-19 on a monthly basis were then analysed Figure 4. This is to enable us to get insight of COVID-19 pandemic impact on the UK unemployment rate as well as the countries' and cities' sentiments.

RESULTS

TEXTBLOB and VADER Classification

In Table 1, the vendor-labelled sentiments served as the baseline for the TEXTBlob and VADER algorithms' sentiment classification, which resulted in classification accuracy scores of 0.35 and 0.56 respectively. VADER algorithm outperformed the TEXTBlob 60% in accuracy, 8% in precision, 60% in recall and 64% in F1-score in matching against Vendor labels. This is due to VADER ability to effectively differentiate positive and negative texts. Thus, VADER sentiment labelling was adopted as the target label for the project.

NAÏVE BAYES Classification

The Naïve Bayes Algorithm best performance architecture was chosen as the baseline model for the project. In Table 1, the architecture without sampling and hyperparameter tuning of TEXTBlob dataset has the lowest performance metrics - accuracy: 0.492, recall: 0.484, F1-score: 0.486 and AUC: 0.648; while VADER dataset without sampling has the highest precision: 0.808; VADER dataset with SMOTE oversampling and hyperparameter tuning has the highest recall: 0.756 and AUC: 0.921. However, the optimal architecture is model-4 with SMOTE oversampling that gives the following optimal metrics- Accuracy: 0.792, Precision: 0.796, Recall: 0.756, F1-score: 0.790 and AUC: 0.921.

Table 1. Performance evaluation of Machine Learning algorithms, showing Naïve Bayes model 4 with SMOTE oversampling VADER labelled dataset as baseline algorithm for the project.

S/n	Model Name	Architecture	Accuracy	Precision	Recall	F1 Score	ROC AUC
1	TEXTBlob (Weighted scores)	W/o Sampling	0.350	0.650	0.350	0.360	
2	VADER (Weighted scores)	W/o Sampling	0.560	0.700	0.560	0.590	
3	Naïve Bayes + VADER Dataset	W/o Sampling	0.774	0.808	0.703	0.764	0.920
4	Naïve Bayes + VADER Dataset	W/SMOTE Oversampling	0.792	0.796	0.756	0.790	0.921
5	Naïve Bayes + VADER Dataset	W/NEARMISS Under-sampling	0.756	0.734	0.745	0.756	0.921
6	Naïve Bayes + VADER Dataset	W/SMOTE Sampling + Hyper-parameter Tuning	0.792	0.795	0.756	0.789	0.921
7	Naïve Bayes + TEXTBLOB Dataset	W/o Sampling	0.697	0.766	0.620	0.679	0.877
8	Naïve Bayes + TEXTBLOB Dataset	W/SMOTE Oversampling	0.500	0.493	0.488	0.495	0.651
9	Naïve Bayes + TEXTBLOB Dataset	W/NEARMISS Under-sampling	0.509	0.480	0.488	0.516	0.651
10	Naïve Bayes + TEXTBLOB Dataset	W/o Sampling + Hyper-parameter Tuning	0.492	0.490	0.484	0.486	0.648
11	Naïve Bayes + VENDOR Dataset	W/o Sampling	0.796	0.784	0.638	0.771	0.903
12	Naïve Bayes + VENDOR Dataset	W/SMOTE Oversampling	0.562	0.534	0.509	0.528	0.707
13	Naïve Bayes + VENDOR Dataset	W/NEARMISS Under-sampling	0.551	0.522	0.519	0.541	0.688
14	Naïve Bayes + VENDOR Dataset	W/o Sampling + Hyper-parameter Tuning	0.599	0.532	0.507	0.525	0.705

Table 2. Performance evaluation of different Deep Learning algorithm models. The optimal model is Bi-LSTM model 2 architecture with an accuracy of 91% and 87% for precision, recall, & F1-score and AUC score of 94%.

S/n	Model Name	Architecture	Accuracy	Precision	Recall	F1 Score	ROC AUC
1	LSTM (Model 1)	GloVe embedding Layer with 100-dimension, vocab-size - 20000, Max length- 128, Model Layer(64), Dropout and Recurrent Dropout=0.4, Dense(32)ReLu, Dropout and Recurrent Dropout=0.4, Dense(32)ReLu, Dense(10)ReLu, Dense(3)Softmax, Learning rate-0.0038, Optimizer-Adams, Loss -Categorical Crossentropy	0.909	0.863	0.862	0.863	0.932

Table 2 continue

2	Bi-LSTM (Model 2)	GloVe embedding Layer with 100-dimension, vocab-size - 20000, Max length- 128, Model Layer(64), Dropout and Recurrent Dropout=0.4, Dense(32)ReLu, Dropout and Recurrent Dropout=0.4, Dense(32)ReLu, Dense(10)ReLu, Dense(3) Softmax, Learning rate-0.0038, Optimizer-Adams, Loss - Categorical Crossentropy	0.914	0.872	0.871	0.872	0.936
3	LSTM/ Bi-LSTM KerasTuner Hyper parameter Tuning (Model Optimization to get top 3 best configuration shown in Table 1c.)	GloVe embedding Layer with 100-dimension, vocab-size - 20000, Max length- 128, Model Layer(32), Dense(units= hp.Int("units", min_value=16, max_value = 512, step=16)) Activation function (activation= hp.Choice("activation", ['ReLu','Tanh']), Dropout (rate =hp.Float("rate", min_value=0.1, max_value = 0.5, step=0.15)), Dense(3) Softmax, Learning rate(learning_rate = hp.Float("lr", min_value =1e-4, max_value=1e-2, sampling = "log")), Optimizer-Adams, Loss - Categorical Crossentropy					
4	LSTM + Best KerasTuner (Model 3)	GloVe embedding Layer with 100-dimension, vocab-size - 20000, Max length- 128, Dense(96)Tanh, Dropout=0.25, Dense(3) Softmax, Learning rate-0.0015, Optimizer-Adams, Loss - Categorical Crossentropy	0.905	0.859	0.857	0.859	0.929
5	Bi-LSTM + Best KerasTuner (Model 4)	GloVe embedding Layer with 100-dimension, vocab-size - 20000, Max length- 128, Dense(48)Tanh, Dense(3) Softmax, Learning rate-0.0003, Optimizer-Adams, Loss - Categorical Crossentropy	0.900	0.850	0.849	0.85	0.924

Table 3. Performance evaluation of the hyper parameter Keras Tuner for LSTM and Bi-LSTM models. The LSTM with Dense layer (36) activation function – Tanh had the best accuracy of 93%.

S/n	Model	Units	Activation	DropOut	Learning Rate	Accuracy Score
1	LSTM	96	Tanh	0.25	0.0015	0.93
2	LSTM	304	ReLu	0.1	0.0002	0.922
3	LSTM	192	ReLu	0.1	0.0001	0.919
4	Bi-LSTM	48	Tanh	False	0.0003	0.923
5	Bi-LSTM	256	ReLu	False	0.0002	0.922
6	Bi-LSTM	400	Tanh	False	0.0002	0.917

Deep Learning Classification

In Table 2, the deep learning architecture model 4 with Bi-LSTM best keras tuner random search had the lowest accuracy: 0.900, precision: 0.850, recall: 0.849 and F1-score: 0.850 and AUC: 0.924 after being trained with different configurations. However, the Bi-LSTM with architecture model 2 had the best performance metrics – Accuracy: 0.914, Precision: 0.872, Recall: 0.871, F1-score: 0.872 and AUC: 0.936.

The best deep learning model as shown in Table 2 is Bi-LSTM architecture model 2. When compared to the baseline model-4 in Table 1, it was observed that its accuracy, precision, recall, F1-score and AUC outperformed the baseline result with 13.35% accuracy, 8.72% precision, 13.20% recall, 9.40% F1-score and 2.13% AUC in Figure 2.

The optimal model was compared with other literatures on sentiment140 COVID-19 dataset (Chandra and Krishna, 2021) and Senwave COVID-19 dataset (Imran et al., 2020a). It outperformed with 9.19% in accuracy LSTM - sentiment140 COVID-19, while in F1-score, 43.46% LSTM, 43.23% Bi-LSTM and 38.76% BERT on Senwave COVID-19 dataset.

Monthly Office of National Statistics Unemployment Rate and Sentiment Analysis

The vendor monthly sentiments of UK twitter users during the pandemic is predominantly neutral sentiments from March 2020 to September, 2021. While the TEXTBlob monthly sentiments are predominantly positive sentiments from March 2020 to September, 2021. However, in Figure 3, VADER monthly sentiments had positive sentiments expressed between March – May, 2020. This was the period the lockdown was newly introduced and people are trying to adjust to the new norm. Then, negative sentiments were expressed predominantly between June – October, 2020 when unemployment rate increased from 4.0% in March 2020 to 4.1% in June 2020 and on steady rise until January 2021. There was a peak period of unemployment rate of 5.2% between October 2020 and February 2021. Thereafter, from February 2021 we had more positive sentiment tweets with a decline in the unemployment rate. This can be attributed to the different policies the UK government had introduced to minimise the impacts of COVID-19 (ILO, 2020).

197,669 tweets are reviewed in United Kingdom countries. 48.68% tweets locations are in England and it shows the most impact. In Figure 4, there were significantly negative sentiments between May 2020 and October 2020. However, people expressed proportionate positive and negative sentiments from November 2020 till September 2021, when the unemployment rate was on a decline from 5.4% peak to 4.2%. 5.52% tweets locations are in Scotland, the people started to express negative

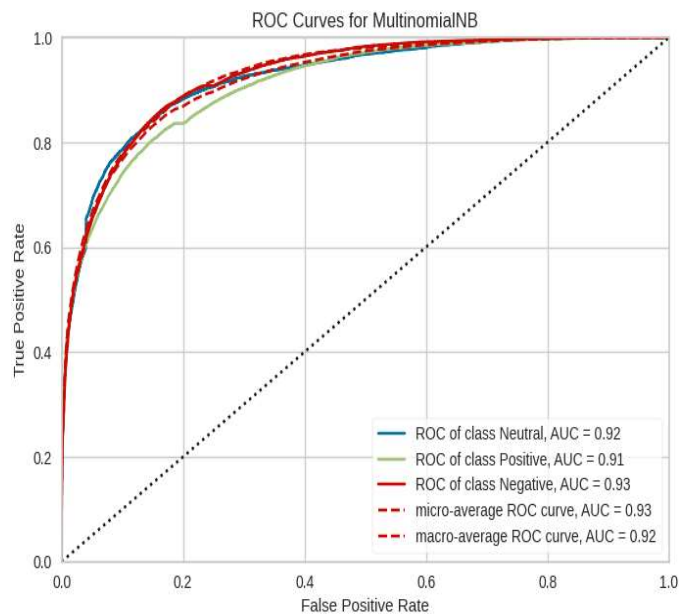


Figure 2a. Naïve Bayes Baseline Algorithm showing the Receiver operating Characteristics Area under curve sentiment class scores. (AUC Score – 92%)

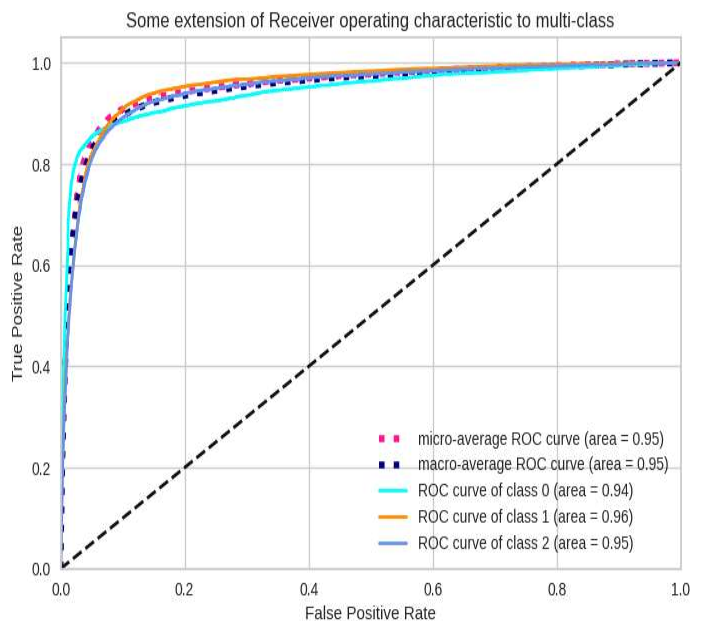


Figure 2b. Bidirectional Long Short-Term Memory Algorithm showing the Receiver operating Characteristics Area under curve sentiment class scores. (AUC Score – 94%)

Figure 2. The baseline Naïve Bayes machine learning algorithm and optimal Bidirectional Long Short-Term Memory deep learning algorithm showing Area under the ROC curve performance of each sentiment class with class 0 as Neutral, class 1 as Positive and class 2 as Negative.

sentiments from July 2020 when the unemployment rate had risen to 4.9% through to February 2021 in a sinusoidal curve. Thereafter, they expressed comparative positive and negative sentiments as the unemployment rate normalised to 4.1%. Wales had 1.81% tweets locations; the people expressed positive sentiments predominantly with the lowest unemployment rate of 3.2%. Northern Ireland had 0.75% tweets location, predominantly with positive and neutral tweets with low unemployment rate (Figure 4e). Furthermore, 43.25% of tweet locations are unknown.

A subsequent drill down shows top 10 cities with the highest responses on Twitter platform on COVID-19 impact on unemployment.

- **London:** In Figure 5, there were significantly negative sentiments from May 2020 when unemployment rate is on the rise till January 2021. Subsequently, there were proportionate positive and negative sentiments as more people got claims and re-employment. London being the most industrialised and populated, the COVID-19 impact is expressed by the negative sentiment and the highest unemployment rate of 5.4%.

- **Glasgow:** There were significantly negative sentiments from May 2020 when unemployment rate is on the rise till February 2021. Then, there were proportionate positive and negative sentiments. This is a huge retail hub city in Scotland and third largest in the UK.

- **Manchester:** There were significantly positive sentiments except October 2020, July 2021 and September 2021 with more neutral sentiments.

- **Cardiff:** There were predominantly positive sentiments except May - June 2020 with more neutral sentiments. The largest city in Wales, with very low unemployment rate prior to COVID-19 which doubled during the pandemic.

- **Edinburgh:** There were significantly neutral sentiments between March - June 2000 and March – April 2021. However, during July – October 2020, the peak unemployment rate of 4.5% they expressed positive sentiments.

- **Bristol:** They expressed significantly neutral sentiments during the pandemic.

- **Birmingham:** There were comparatively negative and neutral sentiments with more negative tweets during peak unemployment rates.

- **Leeds:** There are predominantly negative sentiments. However, there are more positive sentiments in October 2020 peak unemployment rate.

- **Liverpool:** There are comparatively negative and neutral sentiments.

- **Belfast:** There are comparatively positive and neutral sentiments.

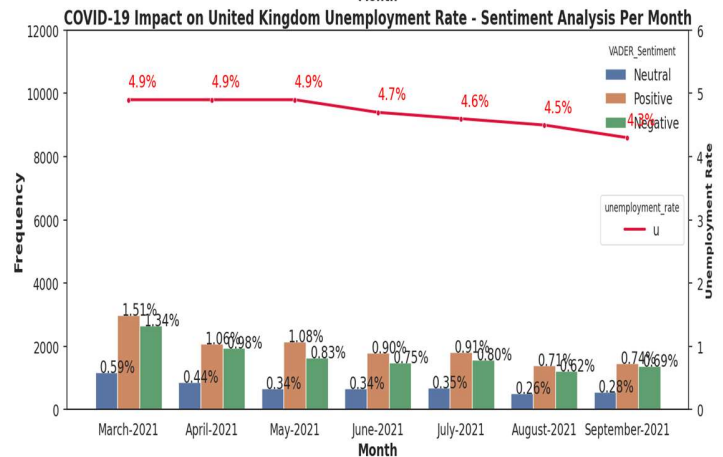
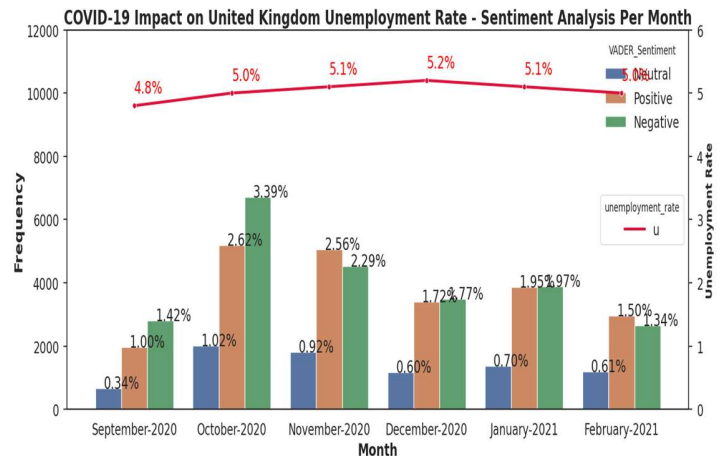
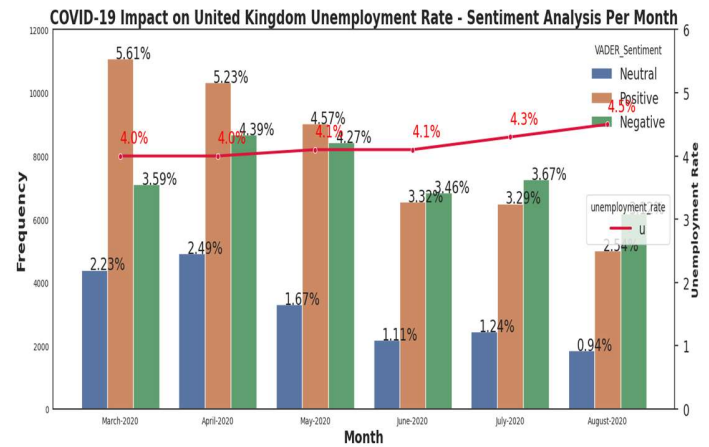


Figure 3. United Kingdom COVID-19 monthly sentiment analysis classified into neutral, positive and negative. The chart shows COVID-19 impact on UK unemployment rate trend with analysis of the sentiments expressed by the people on twitter platform about unemployment between March 2020 and September 2021. It shows more negative sentiments as the unemployment rate increases

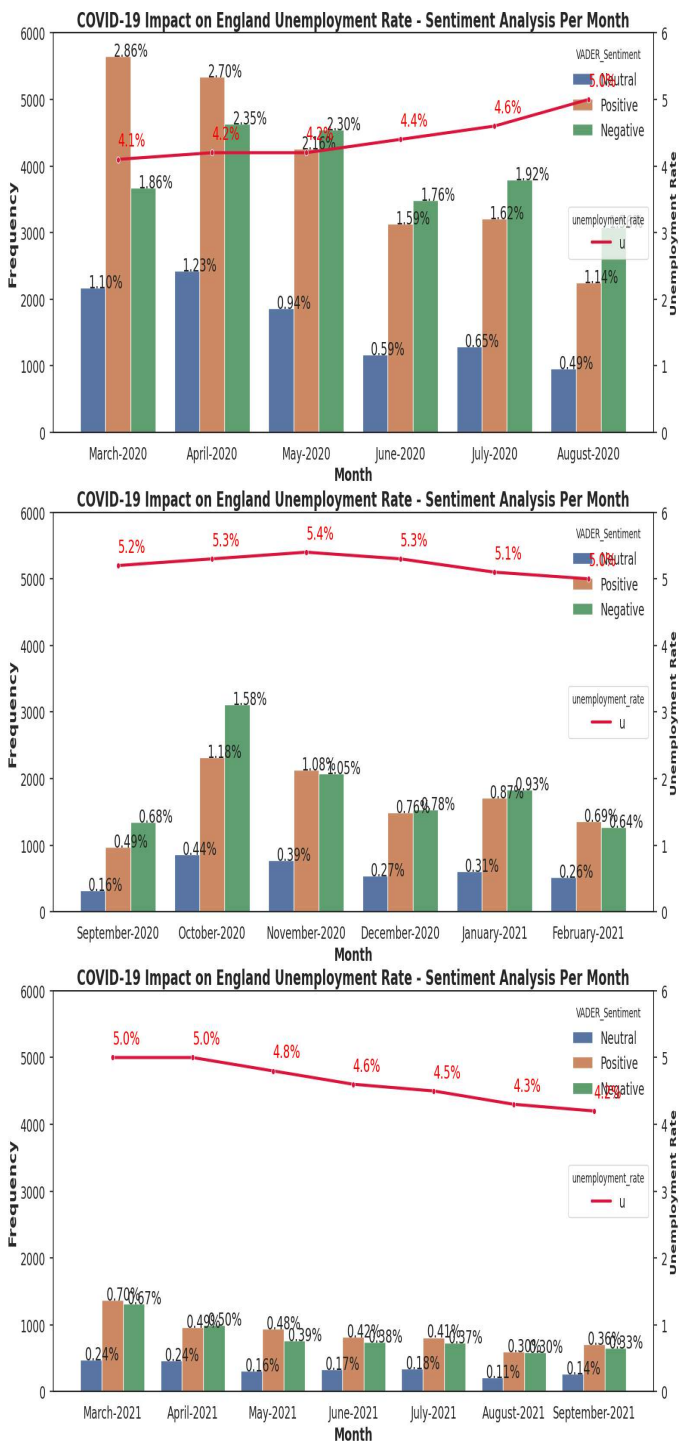


Figure 4. England COVID-19 monthly sentiment analysis classified into neutral, positive and negative. The chart shows COVID-19 impact on England unemployment rate trend with analysis of the sentiments expressed by the people on twitter platform about unemployment between March 2020 and September 2021. It shows more negative sentiments as the unemployment rate increases.

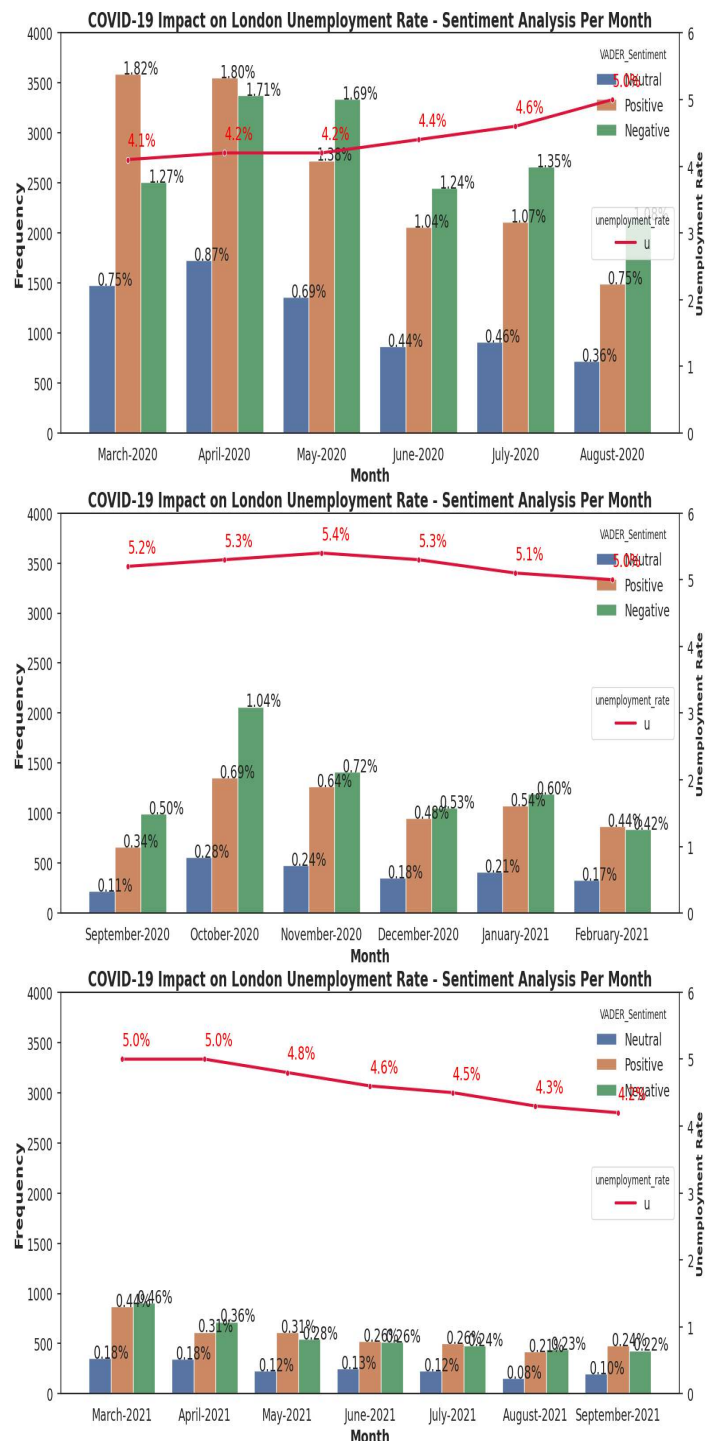


Figure 5. London COVID-19 monthly sentiment analysis classified into neutral, positive and negative. The chart shows COVID-19 impact on London unemployment rate trend with analysis of the sentiments expressed by the people on twitter platform about unemployment between March 2020 and September 2021. It shows more negative sentiments as the unemployment rate increases.

SUMMARY AND CONCLUSIONS

Summary

This study aims to evaluate the performance of the different machine and deep learning models' performance to classify sentiments tweets published during COVID-19 pandemic and its impact on UK unemployment rate. Our findings showed that the Bi-LSTM model outperformed other machine learning models across all evaluated performance metrics. The Bi-LSTM model has an accuracy of 92.55%, AUC score of 93% and 90% in F1-score, precision and recall. Furthermore, our results showed that there were significant negative tweets when the unemployment rate increased.

This study has some limitations. The current study has just looked at Twitter data only, which does not represent more than 30% of the total population of the United Kingdom. As of October 2021, there were approximately 19.05 million users of the Twitter platform, however Facebook had more users (CYBERCREW, 2022). As a result, this research cannot give a complete picture of the entire UK. Furthermore, not all the pertinent tweets conveying crucial views may be found using the hashtags employed to gather the Twitter data. In the sentiment analysis, we also avoided using emojis.

These limitations can be addressed and improved by extending the scope of data source to include Facebook and Reddit platforms, increasing the number of hashtags used to retrieve more tweets, and utilising the information found in emojis in future studies.

CONCLUSIONS

This research was able to ascertain that the monthly sentiments expressed by the people of the United Kingdom at the early stage of lockdown, had positive sentiments towards unemployment. But negative sentiments were predominantly expressed when companies started to lay-off their staff and restrictions on employment. Thus, the unemployment rate soars high. On the other hand, the UK government's effective COVID-19 policies implementations were able to change the sentiments to positive while reducing the unemployment rate. More so, Bi-LSTM RNN approach outperformed other algorithms in this study with unbalanced data. Thus, classification of the sentiments of people on unemployment due to impact of COVID-19 in the UK into neutral, positive and negative was done with an accuracy -91%; precision, recall and F1-score- 87% each and AUC: 94%. Due to the predominance of negative sentiments and reactions on the Twitter platform, the study's findings indicated that England and Scotland, together with their largest cities London and Glasgow respectively, are most

impacted by the pandemic impact on the unemployment rate.

The future work recommended is to use the BERT state-of-the-art model, an ensemble model of LSTM and Bi-LSTM to carry out sentiment analysis of the UK COVID-19 twitter unemployment dataset. Also, a deployment of a real-time application to aid decision making. Furthermore, this study would aid the UK government and other researchers interested in the impact of COVID-19 on other issues such as mental health, social economic and education.

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