Rumour detection in Twitter: Determining useful attributes for classification.

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ABSTRACT With the growth of social media like Twitter in the community, it became easier for people to get data or spread rumours. But developing an automatic moderation system to check the credibility of the data is a challenging work, an alternate approach is with the help of users or third-party organization to flag those tweets which are suspected to be rumours, but this method is highly inefficient and redundant, hence making our social media an unreliable source for Information. As a part of this work, we used three publicly available twitter datasets to find such discriminative features which can classify a tweet as a rumour or non-rumour. Using two recursive neural models and two artificial neural models, the results in the work provides us evident information to correlate important features for classifying the tweets. Along with the result, we have also proposed methods for attributes extraction from user and tweets and pre-processing techniques to retain the key information.

INDEX TERMS Twitter 15 dataset, Twitter 15 dataset, Tweet meta-data attributes, PHEME dataset, Rumor detection, User meta-data extraction.

I. INTRODUCTION

As per Peterson and Warren, a rumour is defined as “a tall tale of explanation of events circulating from person to person and about an object, event, or issue in public concern” [1]. In layman terms, rumour is a statement whose veracity is not confirmed quickly or at all, but it is propagating among a bunch of people. Rumours give birth to the spread of misinformation (false information) or disinformation (deliberate false information) in public. Rumours have been a part of society from historical times. With the birth of new-age technologies and the development of social media sites, the grounds for connectivity have rapidly increased. Among these sites, Twitter has emerged as a leading source of information sharing where on average 500 million tweets are shared per day where each user by design can tweet up to 140 characters long message or share files like pictures or videos. Twitter supports a follower and following design in which a user can subscribe to some other user’s tweets to receive information posted by the latter. Such a system provides a fluent flow of data. These tweets sometimes contain resourceful information like public announcements by governing organizations, sharing of events, personal experiences, beliefs, thoughts and many more, camaflouging among this data, rumours are widely spreading and destroying the credibility of this information. This problem is elevated due to crowdsourcing where a rumour can be backed by many users due to a lack of knowledge regarding the matter and their beliefs. To tackle this issue a lot of work has been done in the research community to find a prominent solution. With this work, we try to understand the root cause of how a rumour is generated on Twitter, its varying nature, way of propagation, the targeted audience and attributes through which it is easier to classify the veracity of the tweet.

We propose three neural network-based solutions to understand the insight in tweet data and to map a trend for the classification task. All the models are developed as a supervised learning task on twitter’s publicly available dataset from which tweet-id and labels are gathered and then using respective tweet-id, tweets are collected in JSON format using Twitter API. Labels in the dataset are categorized into three categories as follows:

* Non-rumour
* True (rumour whose veracity is defined as correct information on a later period, but it started spreading as rumour initially.)
* False (rumour whose veracity is defined as incorrect information or deliberate misinformation after extensive search either from a third-party organization like Politifact or Gossipcop or by flagging such tweets with the help of users.)
* Un-verified (are those rumour spreading tweets whose veracity is still questionable and people are still verifying their states.)

To further investigate the working and develop models a basic understanding of dataset labels was necessary. A general misconception in masses is that fake news or a rumour categorized as false is the only rumour data and to verify this hypothesis we developed a recurrent neural model to find the probability of the tweet text content being fake and understanding a relation. This model is also developed as a supervised learning task on FakeNewsNet [2] dataset, trained nearly on 50,000 tweets. General overviews of the solutions are:

1. User and Tweet meta-data model: is an artificial neural network model which takes users and tweet meta-data and learns the discriminative attributes for the classification task.
2. Tweet text analysis model: is a recurrent neural network model which performs NLP task on tweets text content to understand relevant information for classification
3. Sentimental analysis on the reaction of tweets model: which is a sentiment analysis task to understand to get an average sentiment of the comments on a tweet and then using it as an attribute for rumour classification.
4. Fake or real classification: is also a recurrent neural network model to get the probability of the text being fake or real.

After this, all models were ensembled together and trained on the dataset to get the final weights of all the model. These weights determine how much the rumour classification task is dependent on the models which in turns provides the weight to understand the importance of different tweet attributes. Overall the contributions are mainly in eight aspects.

1. Proposing a feature extraction mechanism and preprocessing techniques to make data more relevant.
2. Developing a hypothesis on metadata in user and tweet dataset and mapping the relation to the problem
3. Two NLP models to understand the text features, emotion, POS, general topic and other attributes for rumour and fake tweet classification
4. Correlating derived and extracted feature to realize the relationship between attributes and reduce the dimensionality of efficient resource utilization
5. Ensembling techniques for combining the models and training and testing the final model for a general solution
6. Understand the weight distribution of feature variables and formulating their importance.
7. Defining loss metrics for the classification task on the dichotomous rumour data.

II. RELATED WORKS

In this section, the background research and studies conducted by us to understand the problems still persistent in rumour studies and how we formulate the problem statement is provided. We firstly introduce the research done in the field to provide some context to the reader, then we shift focus on the past works done to analyze the rumour spread and detection in Twitter. Some state-of-the-art overview in this research domain is:

1. ***THEORIES OF RUMOR TRANSMISSION***

Allport and portman in their earlier work psychology of rumour” [3] stated that “rumours become more concise, easy to grasp and told as it propagates.” In this work, the rumour life cycle is divided into three phases namely levelling, sharpening, and assimilation. They gave a law of rumour that provides a basic relation between rumour transmission state and the importance of the topic. It is stated as:

Where R, i and a denote rumour spread intensity, the importance of the topic, and ambiguity, respectively. It means that if the rumour topic is not important to a certain audience, then the spread comes to a halt in that group. Generally, the emergence of a rumour is to fulfil a particular function.

1. ***PREVIOUS WORK***

Castillo et al. [4] is one of the earliest works in developing a statistical and automatic approach to detect rumours to learn and engineer a wide range of attributes from posts, user profiles and patterns of tweet propagation to develop a supervised classifier for detection. Works by Margolin et al.,Hannak et al. conducted studies to craft new features representing rumour diffusion and to know when corrections have an effect on the Political Fact-checking dataset [5] . Liu et al., K. Wu et al., Yang et al. [6] used a time-series model on tweets with varying propagation time. Kwon et al. [7] introduced numerous sets of features from various perspectives. As the field of AI is emerging, a few researchers are striving to recognize rumours through deep learning, Ma et al. [8] and Rath et al. [9] made a model using a Recurrent neural network of deep learning to understand the abstract expression of rumours. Guo et al. [10] combined feature engineering and deep learning model to form a hierarchical social attention model that led to the improvement of rumour detection models. The most critical challenge of rumour detection is the early detection of rumours, Wang et al. [11] and Kwon et al. proposed a probabilistic model based on the eminent features of propagation of rumours. It was found that the user and linguistic features can be used as principal methods to indicate rumours. Along with the traditional models, deep learning and machine learning have been applied to detect rumours early. Wu et al. [12] made a model capture high-order propagation patterns using a graph-kernel based hybrid SVM classifier. Zhao et al. [13] proposed a technique for searching enquiry phrases with high performance. Zhang et al. [14] developed an early rumour detection heterogeneous network that yielded 61% precision. T. Chen et al. [15]made a soft-attention structure using RNN. L. Wu et al. [16] made a neural network model. They deduced rumour categories, selected discriminative features and learnt a rumour classifier. Nyugen et al. [17] proposed a CNN for understanding the hidden representations of each tweet when combined with a time series.

III. CONCEPTUAL BACKGROUND

In this section, we introduce the four hypotheses which we assumed to have a good and discriminative effect on the detection of rumour in tweets.

1. ***USER TWEET METADATA***

In this hypothesis, we have used combined metadata of the user database and tweet database. We explored various features and tried extracting more discriminative features from the already existing ones in the database. We further analysed the extracted features for understanding the data and for performing feature selection.

1. LOG TRANSFORM (METHOD FOR CONVERTING SKEWED FEATURES INTO NORMAL DISTRIBUTIONS)

Incrementing all the non-categorical skewed features by one followed by performing log transformation on non-categorical skewed features, which converts the data into a normal distribution. Normal distribution ensures that more reliable predictions are made from the available data. The non-categorical skewed features were incremented by 1 to avoid the mathematical error of which is undefined.

1. POINT BISERIAL CORRELATION

Point Biserial [18] is a special case of Pearson’s correlation. It is used to find the correlation between a continuous variable and a binary variable.

where,

= M[ean](https://www.statisticshowto.com/mean/) of the group that received a positive binary variable.

= Mean of the group that received a negative binary variable.

= Standard deviation [19]

= Proportion of cases in the “0” group

= Proportion of cases in the “1” group

The resultant correlation coefficient ranges between 0 and 1.

If,

, then it signifies a positive correlation between the features.

, then it signifies a negative correlation between the features.

then it signifies no correlation between the features.

1. MUTUAL INFORMATION

Mutual Information [20] is a measure of mutual dependence between two features, it uses the theory of entropy.

The entropy of a discrete variable with pmf is,

[ log(p(y))]

If we have two random variables and , the joint entropy is given by,

x, y) log(p(x,y))

It measures the uncertainty in the two variables and .

The conditional entropy of given is,

It measures the uncertainty of when we know.

The mutual information of two random variables and jointly distributed to is given by

1. ***B. TEXT DATA OF TWEETS***

In this hypothesis, we use text in tweets to create a model which supports the detection of rumours in tweets.

1. WORD EMBEDDINGS

It is a representation of words in the form of a real-valued vector. It is encoded such that words with similar meaning get closer vectors in the vector space. We have used an open-source pre-trained word embedding called [fastText](https://fasttext.cc/) [21] .

***C. FAKE OR REAL***

In this hypothesis, we use the text data to determine the probability of the data being fake or real. Example: - “If person X tells person Y that person Z is smart, this news is still a rumour to person Y. Later, if person A tells person Y that the news that person Z is smart is true, then the probability of being a non-rumour of the news that person X told to person Y about person Z increases.”

The methods used in the process of training this model is similar to that of the [text data of the tweets](https://docs.google.com/document/u/0/d/1QFlvMXTtwVQ6KyCvDN4uSu6hgXQsncSx3Qyz2PTqoG4/edit) model.

***D. SENTIMENT ANALYSIS ON THE REACTION OF TWEETS***

In this hypothesis, we use the reaction data linked with the tweets. Sentiment analysis has been done on the text data of the reactions linked to the tweets and polarity received from the analyser is weighted by multiplying with metadata variable values of the reaction.

Now, architecture, various hyperparameters relating to the models will be explained.

***E. ARCHITECTURE***

1. ACTIVATION FUNCTIONS

The activation function of the layer determines the output of the layer given a set of inputs. Activation functions used in the implemented neural network models are.

* Relu
* Sigmoid

Relu [22]: It gives the output directly if the output is positive else gives 0.

The output ranges between .

Sigmoid [23] :

It is a real, bounded, and differentiable function defined for all input values. The output ranges between .

1. WEIGHT INITIALIZATION

Weight initialization is a procedure to set the initial weights of a neural network using different methods. Weight initialization methods used in the implemented neural network models are.

* He-normal
* Glorot normal

He-normal [24]: In this method of weight initialization, weights are initialized by considering the size of the previous layer. This helps in faster and accurate gradient descent.

It draws weights from a normal distribution centred on 0 and with a standard deviation as calculated from the formula below.

For relu,

where,

, is the output of layer before applying activation function.

,, are weights of respective nodes .

, is the number of inputs units.

He-normal is used with relu activation functions in the implemented neural networks.

Glorot-normal [25]: In this method of weight initialization, we use fan-in and fan-out to determine the initial weights of the nodes. It draws weights from a normal distribution centred on 0 and with a standard deviation as calculated from the formula below.

where,

, is the number of inputs units.

, is the number of outputs units.

Glorot-normal is used with sigmoid activation functions in the implemented neural networks.

1. BATCH NORMALIZATION

Batch Normalization [26] is a technique that transforms the data in a way that it has a mean of 0 and a standard deviation of 1. In cases where the input to the initial layer of the neural network is already normalized, the output from the activation functions might no longer be on the same scale and hence causing internal covariate shifts in the data. Batch normalization is applied to each input to avoid this problem.

Batch normalization is a two-step process. First, we normalize the input and later rescaling and offsetting is performed.

We first compute the mean using the input from the i-th layer,

where,

, are the inputs from layer h

, is the number of neurons in layer h.

Next, we calculate the standard deviation of hidden activations.

Now, we subtract the mean from each input and divide by the sum of standard deviation and smoothing term to get the normalized data.

In the final operation, we use rescaling parameter and shifting parameter .

1. LOSS FUNCTIONS

The loss function is used to determine the error between the output and the desired output. The primary loss function used for classification problems is cross-entropy. We categorize tweets into either rumour or non-rumour so, it has only 2 outputs. Hence, binary cross-entropy [27] is used.

where,

is the desired output.

, is the predicted output.

1. ADAPTIVE MOMENT ESTIMATION (ADAM)

Adam [28] is a combination of gradient descent with momentum and RMSProp. It gets smoothening factor from momentum and adaptive learning rate like in RMSProp.

First, we calculate the weighted average of past gradients,

where,

, the exponentially weighted average of past gradients.

, the exponentially weighted average of past gradients of bias.

, cost gradient for the current layer.

Next, we calculate the exponentially weighted average of the squares of past gradients.

, the exponentially weighted average of past squares of gradients.

, the exponentially weighted average of past squares of gradients of bias.

Calculated averages have a bias towards zero so to fix this we use the technique of bias correction.

Now, the final formula for the weights will be calculated as follows.

IV. EXPERIMENTS

In this section, the overall research is divided into 5 parts. The parts are divided based on the hypotheses. Each part will contain details regarding the database used, pre-processing, selected features, the model used.

1. ***TWEET TEXT ANALYSIS MODEL***
2. DATABASE

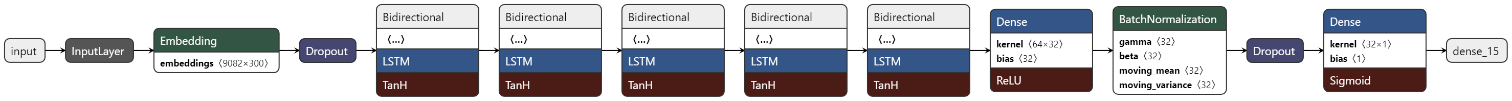
In this hypothesis, the combination of PHEME [29], Twitter 15 [30] and Twitter 16 [31] [32] is used.

1. PRE\_PROCESSING

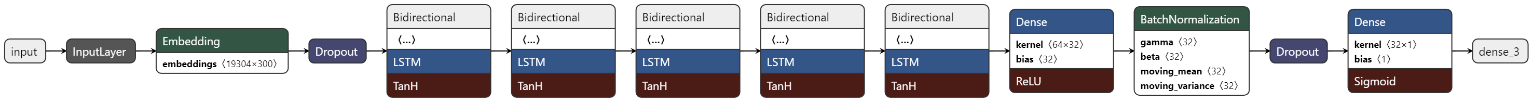
Initially, we used the [tweet-pre-processor](https://pypi.org/project/tweet-preprocessor/)[33] library of python to remove links, emojis, numbers. Next, we used the [contractions](https://pypi.org/project/contractions/) [34]library of Python to replace the contracted words with their expanded forms. Next, we pre-compiled a list of abbreviation which are commonly used in tweets and then we replaced the abbreviated words in Tweet text with their true forms. Next, we used the [wordsegment](http://www.grantjenks.com/docs/wordsegment/) [35] library of Python to remove mentions, removing the hashtags and splitting the text in the hashtags. Next, we removed the stop words using a pre-defined list. Next, we used the [Tokenizer](https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/text/Tokenizer) [36]library of Python to fit on texts and then convert them to sequences. We further padded the size of the sequences to a size that is equal to the sum of the mean of cleaned tweets length and standard deviation of the length of cleaned tweets. We have used fastText word embeddings to create the embedding matrix which is further passed into the neural network.

1. TRAINING AND MODEL ARCHITECTURE

We have used a sequential TensorFlow model. The first layer in the model is an Embedding layer which takes the embedding matrix, embeddings dimension, input length as inputs. Next, we have used a dropout layer with a value of 0.5. Next, we have used 4 layers of Bidirectional LSTM with 64 nodes in each with return sequences turned on. We further have 1 layer of Bidirectional LSTM with 32 nodes. Then, we have a dense layer with 32 nodes and a relu activation function. Next, we have a layer of Batch Normalization which is processed with a dropout layer with a value of 0.5. Further, we have the final layer which is a dense layer with 1 node with the activation function of the sigmoid. This model is compiled with Adam optimizer and the loss used is binary cross-entropy.



**FIGURE 1: ANN architecture of Tweet text analysis model**



**FIGURE 2:** **ANN architecture of Fake or Real Classification model**

The accuracy metrics used is accuracy. The model summary is as follows.

|  |  |  |
| --- | --- | --- |
| **Layer(Type)** | **Output Shape** | **Param#** |
| embedding (Embedding) | (None,93,300) | 2724600 |
| dropout(Dropout) | (None,93,300) | 0 |
| bidirectional(Bidirectional LSTM) | (None,93,128) | 186880 |
| Bidirectional\_1(Bidirectional LSTM) | (None,93,128) | 98816 |
| bidirectional\_2(Bidirecitonal LSTM) | (None,93,128) | 98816 |
| bidirectional\_3(Bidirecitonal LSTM) | (None,93,128) | 98816 |
| bidirectional\_4(Bidirecitonal LSTM) | (None,64) | 41216 |
| dense(Dense) | (None,32) | 2080 |
| batch\_normalization(BatchNormalization) | (None,32) | 128 |
| dropout\_1(Dropout) | (None,32) | 0 |
| Total params: 6,317,985 | | |
| Trainable params: 526,721 | | |
| Non-trainable params: 5,791,264 | | |

This data was split into test and train with a test size of 0.2, random state of 42 and stratified for the target labels.

The model was trained with the X\_train padded sequences and y\_train and with validation data ( X\_test padded sequences, y\_test). The batch size taken is 128 and trained for 150 epochs with an early stopping monitoring for minimum validation loss with patience of 5.

1. ***FAKE OR REAL CLASSIFICATION MODEL***
2. DATABASE

In this hypothesis, the FakeNewsNet dataset is used.

1. PRE\_PROCESSING

The pre-processing is the same as the Tweet text analysis model.

1. TRAINING AND MODEL ARCHITECTURE

The model used here is the same as the tweet text analysis model. Only the number of word embeddings is changed due to different sizes of databases. This model summary is as follows.

|  |  |  |
| --- | --- | --- |
| **Layer(Type)** | **Output Shape** | **Param#** |
| embedding (Embedding) | (None,84,300) | 5791200 |
| dropout(Dropout) | (None,84,300) | 0 |
| bidirectional(Bidirectional LSTM) | (None,84,128) | 186880 |
| Bidirectional\_1(Bidirectional LSTM) | (None,84,128) | 98816 |
| bidirectional\_2(Bidirecitonal LSTM) | (None,84,128) | 98816 |
| bidirectional\_3(Bidirecitonal LSTM) | (None,84,128) | 98816 |
| bidirectional\_4(Bidirecitonal LSTM) | (None,64) | 41216 |
| dense(Dense) | (None,32) | 2080 |
| batch\_normalization(BatchNormalization) | (None,32) | 128 |

|  |
| --- |
| Total params: 6,317,985 |
| Trainable params: 526,721 |
| Non-trainable params: 5,791,264 |

This data was split into test and train with a test size of 0.2, random state of 42 and stratified for the target labels.

The model was trained with the X\_train padded sequences and y\_train and with validation data ( X\_test padded sequences, y\_test). The batch size taken is 256 and trained for 150 epochs with an early stopping monitoring for minimum validation loss with patience of 5.

1. ***USER AND TWEET METADATA MODEL***
2. DATABASE

In this hypothesis, the combination of PHEME, Twitter 15 and Twitter 16 is used

1. PRE\_PROCESSING

The data was analysed and the features with skewed data were log-transformed to get a normal distribution. Next, the pre-processing of text is done similar to the tweet text analysis model. Further, the text was also lemmatized. We used [TextBlob](https://textblob.readthedocs.io/en/dev/) [37] to find the sentiment polarity of the text. Next, we calculated the text length and tweet-age features. Next, we calculated the Posted\_in feature which is the time gap in which the user created the profile and posted the tweet. The final feature list is.

|  |  |
| --- | --- |
| **Numerical Features** | **Categorical Features** |
| Follower’s count | Is\_reply |
| Retweet count | Verified |
| Favourite count | Is\_quote\_status |
| No: of Symbols | Profile\_image\_url |
| No: of User mentions | profile\_background\_image\_url |
| No: of Hashtags | Default profile image |
| No: of URL’s | Default profile |
| Polarity | Profile\_use\_background\_image |
| Text length | Has\_location |
| Post age | Has\_url |
| Statuses count |  |
| Friends count |
| Favourites count of user |
| Listed count |
| Account age |
| Screen name length |
| The time gap between user-created time and tweeted time (Posted\_in\_time) |

In total, we have 27 features. We performed feature selection on these features and arrived at the final features.

Chart

Description automatically generated

**FIGURE 3:** **Correlation between numerical features and the target variable of the user and tweet metadata model derived from point biserial correlation.**

Chart, bar chart, histogram

Description automatically generated

**FIGURE 4:** **Correlation between categorical features and the target variable of the user and Tweet metadata model derived from Mutual information correlation.**

A picture containing chart

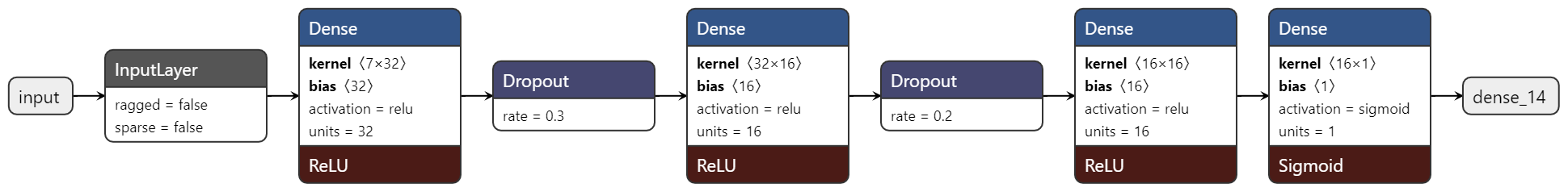
Description automatically generated

**FIGURE 5:** **Correlation between all the features available in User and Tweet metadata model**

A picture containing graphical user interface

Description automatically generated

**FIGURE 6:** **ANN architecture of User and Tweet metadata model**



**FIGURE 7:** **ANN architecture of sentiment analysis model**

The final list of selected features after feature selection is,

|  |  |
| --- | --- |
| **Numerical Features** | **Categorical Features** |
| Text Length | Profile\_use\_background\_image |
| No: of URL’s | Profile\_background\_image\_url |
| Post age | Default\_profile\_image |
| Statuses count | Default\_profile |
| Listed count | Verified |
| No: of symbols |  |
| Posted\_in |
| No: of user mentions |
| Polarity |
| Favourites count of user |
| Favourite count of a tweet |
| Screen name length |
| No: of hashtags |

1. TRAINING AND MODEL ARCHITECTURE

First, we applied a Standard scaler to the selected features. We have used a sequential TensorFlow model. The first layer is a dense layer with 64 nodes, relu activation function and L2 regularization with a value of 0.01. Next, we have a dropout layer with a value of 0.3. Further, we have a dense layer with 64 nodes, relu activation function and L2 regularization with a value of 0.01. Next, we have a dropout layer with a value of 0.3. The final layer is a dense layer with a sigmoid activation function and glorot\_uniform weights initializer. The model is compiled with Adam optimizer, having binary cross-entropy loss and metrics as accuracy. This model summary is as follows.

|  |  |  |
| --- | --- | --- |
| **Layer(type)** | **Output Shape** | **Param #** |
| dense\_1(Dense) | (None,64) | 1216 |
| dropout\_1(Dropout) | (None,64) | 0 |
| dense\_2(Dense) | (None,64) | 4160 |
| dropout\_2(Dropout) | (None,64) | 0 |
| dense\_3(Dense) | (None,1) | 65 |
| Total params: 5,441 | | |
| Trainable params: 5,441 | | |
| Non-trainable params: 0 | | |

This data was split into test and train with a test size of 0.2, random state of 42 and stratified for the target labels.

The model was trained with scaled X\_train values and y\_train. The batch size taken was 32 and validation data was (X\_test\_scaled,y\_test).

1. ***SENTIMENTAL ANALYSIS ON REACTION OF TWEETS MODEL***
2. DATABASE

In this hypothesis, the PHEME dataset is used. There is no reaction data in Twitter 15 and Twitter 16 datasets. The lack of this data is compensated while combing the models.

1. PRE\_PROCESSING

The text comments on the tweets are cleaned and pre-processed like the tweet text analysis model and further, it is lemmatized. TextBlob Python library was used to find the polarity of the comments on the tweets. We multiplied these polarities with favourite count, retweet count, sum of favourite count and retweet count to get 3 weighted averages of polarities. Retweet count, Favourite count, No: of hashtags in the text of comments are also taken in the total features list. The total list of features are.

|  |
| --- |
| Retweet Count |
| Favourite count |
| Sentiments |
| No: of hashtags |
| Favourite weighted polarity |
| Retweet weighted polarity |
| Favourite retweet weighted polarity |

After performing feature selection, it was observed that Favourite weighted polarity, retweet weighted polarity and favourite retweet weighted polarity had a similar negative correlation to the label.

So, we only took the main polarity(sentiments) feature during feature selection.

The final list of selected features is.

|  |
| --- |
| Favourite count |
| Sentiments (Polarity) |
| No: of hashtags |

This data is scaled using Standard Scaler after splitting it into test and train.

1. TRAINING AND MODEL ARCHITECTURE

We have used a sequential TensorFlow model. The first layer is a dense layer with 32 nodes and a relu activation function. Second, we have a dropout layer with a value of 0.3. Third, we have a dense layer with 16 nodes and a relu activation function. Fourth, we have a dropout layer with a value of 0.2. Fifth, we have a dense layer with 16 nodes and a relu activation function. Sixth, we have the final layer which is a dense layer with a sigmoid activation function.

This model is compiled with Adam optimizer and binary cross-entropy is taken as loss function. The metric used is accuracy. The model summary is as follows.

|  |  |  |
| --- | --- | --- |
| **Layer(type)** | **Output Shape** | **Param #** |
| dense\_1(Dense) | (4598,32) | 256 |
| drouput\_1(Dropout) | (4598,32) | 0 |
| dense\_2(Dense) | (4598,16) | 528 |
| dropout\_2(Dropout) | (4598,16) | 0 |
| dense\_3(Dense) | (4598,16) | 272 |
| dense\_4(Dense) | (4598,1) | 17 |
| Total params: 1,073 | | |
| Trainable params: 1,073 | | |
| Non-trainable params: 0 | | |

This data was split into test and train with a test size of 0.2, random state of 42 and stratified for the target labels.

The model was trained with scaled X\_train values and y\_train. The batch size taken was 32 and validation data was (X\_test\_scaled,y\_test).

1. ***ENSEMBLE MODEL COMBINING THE ABOVE MODELS***
2. DATABASE

In this hypothesis, the combination of PHEME, Twitter 15 and Twitter 16 is used.

1. TRAINING AND MODEL ARCHITECTURE

We have extracted the predicted probabilities of each model on the complete dataset and treated them as separate features to train a model. Due to the lack of complete data of reactions on tweets, we have assumed a predicted probability of 0.5 on the data which is present in the Twitter 15 and 16 dataset but not in the PHEME dataset. We have used a sequential TensorFlow model. The first layer is a dense layer with 64 nodes and a relu activation function. The second is a dropout layer with a value of 0.3. Third, is a Dense layer with 64 nodes and a relu activation function. Fourth, is a dropout layer with a value of 0.3. The fifth and final layer is a dense layer with 1 node, sigmoid activation function and glorot\_uniform weight initializer.

The model is compiled using Adam optimizer and binary cross-entropy as loss function. The metrics used are accuracy. The summary of the model is as follows.

|  |  |  |
| --- | --- | --- |
| Layer (Type) | Output Shape | Param # |
| dense\_1(Dense) | (None,64) | 256 |
| droupout\_1(Dropout) | (None,64) | 0 |
| dense\_2(Dense) | (None,64) | 4160 |
| dropout\_2(Dropout) | (None,64) | 0 |
| dense\_8(Dense) | (None,1) | 65 |
| Total params: 4,481 | | |
| Trainable params: 4,481 | | |
| Non- trainable params: 0 | | |

V. RESULTS

The results of each of the models discussed in the experiments section are shown in this section. Note: The predict probabilities of the Fake tweet classification model do not predict if a tweet is a rumour or a non-rumour, they support the ensemble model to get better accuracy. Hence, the accuracy of the Fake Tweet classification won’t be taken into consideration in the process of analysing the results.

1. ***RESULTS OF THE MODELS OF THE 4 HYPOTHESES AFTER TRAINING***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Loss** | | **Accuracy (in %)** | |
| **Training** | **Validation** | **Training** | **Validation** |
| Tweet text analysis model | 0.274 | 0.449 | 88.6 | 80.1 |
| Fake tweet classification model | 0.074 | 0.084 | 97.3 | 97.4 |
| User and tweet meta data model | 0.469 | 0.550 | 77.5 | 74.5 |
| Sentiment analysis on reaction of tweets | 0.644 | 0.647 | 63.5 | 63.6 |

1. ***RESULTS OF ENSEMBLE MODEL***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Loss** | | **Accuracy(in%)** | |
| **Training** | **Validation** | **Training** | **Validation** |
| Ensemble Model | 0.270 | 0.430 | 88.88 | 81.8 |

1. ***CHART COMPARING THE RESULTS OF ENSEMBLE MODEL AND OTHER MODELS***
2. ***FEATURE IMPORTANCE OF FEATURES IN USER TWEET METADATA MODEL***

The database used in the User Tweet metadata model is fitted on a decision tree classifier. The inbuilt feature\_importances\_ function of the decision tree classifier is used to get the score of feature importance

1. ***FEATURE IMPORTANCE OF EACH MODEL IN THE ENSEMBLE MODEL***

The combined data is fitted on a decision tree classifier. The inbuilt feature\_importances\_ function of the decision tree classifier is used to get the score of feature importance.

Due to the limited availability of data, the ensemble model is overestimating the importance of the Tweet Text model. This can be improved by live training the model with live data or by manually editing the weights in the ensemble model.

1. ***PREDICTION ACCURACY ON UNSEEN TEST DATA***

From the initial database, we kept aside 1038 tweets from the combined dataset of PHEME, Twitter 15 and 16 to finally use it as random unseen data for testing. The predicted accuracies of each of the models are as follows.

From this, we can see that the text model is not very useful on unseen and live data but due to the limited availability of labelled datasets, this is a limitation for the ensemble model to learn better. Out of 1038 tweets, only 720 of them had the reaction of tweets data. So, the sentiment model could only predict for 720 inputs. The accuracy obtained on the 720 inputs is 64.17%. But we have assumed an accuracy of 50% on the remaining 318 tweets. So, this has resulted in the accuracy of the sentiment model to go down to 59.82%.

The accuracy could have been better if the reaction data of tweets were available for the remaining 318 tweets. The mathematics of how the new accuracy of 59.82% was calculated as mentioned below.

We have taken the weighted mean to calculate the adjusted accuracy of the sentimental analysis of the reaction of tweets model.

VI. CONCLUSION, CHALLENGES AND FUTURE WORK

Upon testing the models on unseen data, we can safely conclude that the ensemble model is overestimating the importance of the Tweet text model due to the limited availability of data. We can also see that Sentimental analysis of tweets model and User Tweet metadata model perform better on unseen data compared to the Tweet text model. Live training of the ensembled model and manual weight adjustment can improve the accuracy of the model.

Future work to make the models better include live training of ensembled model on live data to improve the accuracy of the model, better analysis of comments on tweets by classifying them into supportive, rejective, question comments, retrieving more labelled datasets to make the models understand better.

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**A person in a white shirt

Description automatically generated with low confidence**

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A person wearing glasses

Description automatically generated with medium confidence

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