Text Similarity-Based approach to detect Sinhala Language Fake News in Social Media: An approach using Hybrid Features

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Abstract— **In this rapidly evolving digital age, societies rely heavily upon social media to share news publicly due to the speed of dissemination. With billions of users, the sharing of a news item only takes a few minutes to represent diverged views, with malicious or misleading content, to go viral. In 2018, Sri Lanka experienced anti-Muslim riots, and in 2019, racist uprisings initiated fake news in social media mainly in Sinhala language. Considering the massive number of Sinhala language posts shared at present and the deficiency of research work in Sinhala fake news detection, an automatic fake news detection technique is proposed in this research that can help to identify fake news published in the Sinhala language which circulates on social media sites. Approaches to detect fake news depend heavily upon features inherent to either the explicit or implicit features of user account and text content-based features of the post, or any hybrid set of above features. Based on the literature, social media users mainly consider verifiability to identify fake news content. Therefore, the hybrid methodology proposed in this research work mainly focused on the checking and verifying whether the news text content appears on the credible sources. The authenticity features of the user account that used to obtain the news content were evaluated in the rule-based points allocation schema. An accuracy of 78% was gained in predicting fake news with this Rule-Based implementation.**

Keywords: Fake News, Social Media, Hybrid Methodology, Rule-Based

I. INTRODUCTION

With the rapid growth in internet technologies in the past ten years, social media has been observed is indicative of the importance and has become a need in people's lives. As a result of the enhancement of internet facilities provided by Internet Service Providers (ISP), people tend to use online sources, including social media and websites of famous newspaper publishers as sources of journalism. The rapid transformation of traditional print media into online portals becomes a new trend. From the above reasons, because of the easy accessibility of social media than that of other websites, people started to use social media networks such as Facebook, Twitter, and Instagram for reading and sharing posts on news articles.

A. Social Media Usage

The websites and mobile applications designed to allow people to share content rapidly and connect with others efficiently and in real-time come under social media platforms. In the world, more than 4.5 billion people were using the Internet at the beginning of 2020. Among them, 3.8 billion people can be identified as social media users. Nearly 60% of the global population uses the Internet for various day-to-day activities. The predictions say that half of the total population of the world will be using social media by the middle of this year. Sri Lanka had about 10 million internet users by January 2020. The number of internet users in Sri Lanka increased by 399,000 between 2019 and 2020. It is a 4.3% of risen of value than in the previous year. According to statistics, the internet-using community of Sri Lanka had about 6 million social media users by January 2020. The number of social media platform users has risen by 49,000 (+8.3%) from April 2019 to January 2020 [1].

B. Fake News Problem

Fake news can be defined as fabricated information that imitates news media content but not with the intentions of using in an organizational process according to Lazar et al. Fake news is an invented form of news or the creation of a lie with the intention of deceiving a group of people. Fake news always takes the appearance and copy characteristics of real ones to make people believe in them [2].

Sri Lankan government banned social media for nine days in 2019 during the crisis period of the Easter Sunday attack to stop spreading violence over the Muslim community in the country. The government identified that intentionally publishing fake news may have influenced these violent situations. As a result of this tragedy, the Sri Lankan government introduced five-year jail terms or over one million Sri Lankan rupees fine for those caught spreading fake news and hate speeches on social media platforms [3].

C. The need of Sinhala language Text Monitoring

During the Easter Sunday attacks, though the Sri Lankan government took necessary actions to stop spreading misleading and fake information mainly in Sinhala language in social media by banning social media networks, the effectiveness of that action was very low. There was an increment of postings via the Facebook pages of Sri Lanka during that period as in Fig. 1.[4].

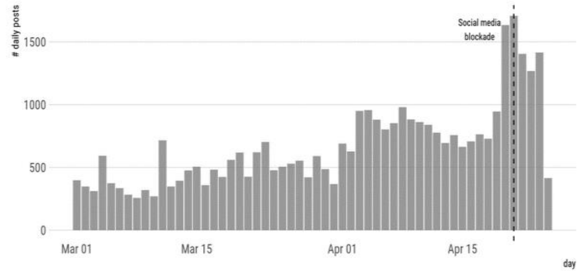

Fig.1. Impact on Facebook postings during the ban of social media in Sri Lanka [4]

When sharing fake information, social media, public pages, and groups are a bigger target because they can have a broad audience. The social media ban appeared to be ineffective to stop spreading misinformation because many users continue to access social media networks using Virtual Private Network (VPN) tools.

The Democracy Reporting International organization conducted a research on Facebook data to understand about the social structure/behavior of Sri Lanka. They did an analysis using Ethno-nationalist pages on the Facebook platform. They collected the top 200 posts of each page and found that misleading content on ethno-nationalist pages was shared more than credible information. The analysis revealed that misleading content in ethno-nationalist pages were shared more than credible information [5]. The organizations providing services as fact-checking for Sinhala, such as Fact crescendo-Sri Lanka and Watchdog-Sri Lanka, also use a manual Verification-Based method. After Social media banning incidents, Facebook hired Sinhala moderators and translators, but still there is a need for an Automatic mechanism for Sinhala Fake News detection. The main objective or the purpose of this research is to introduce an automated methodology to detect social media posts in Sinhala language which have been posted with the intention of misleading people and manipulating public opinion.

II. LITERATURE REVIEW

The work on checking content credibility can be classified based on the features used for credibility assessment. Related work can be divided as:

A. User/Social Account related approach
B. Text/News content related approach
C. Hybrid approach – A combination of features of above two approaches.

A. User/Social Account related approach

The research was conducted on fake news that uses and exploits user-profiles and spread of misleading news [6]. The datasets were collected from two platforms designated for fact-checking, which contains news content labeled by professionals and social context information. These dataset items included text content and user postings/sharing news on Twitter.

Then, the user groups' profile features were extracted, which can help differentiate fake news from real news. The authors identified different subsets of users based on re-tweeting and liking behaviors. After identifying user sets that are more likely to share fake/real news, further comparison and analyzing were done on the degree of the differences of their profiles to find user profile features. The user account features were analyzed from different viewpoints, such as implicit and explicit.

Here Implicit features can be defined as features that are not directly available but are deduced from user meta-information or online behaviors. Ex: Age, personality, profile pictures, location, and political bias. Explicit features are the ones that can be directly obtained from meta-data returned by querying social media site APIs. Ex: Registered date of the account, Status Count: the number of posts, the number of favorites, Follower Count, Following Count, Number of friends.

The authors also analyzed the relative importance of these features for predicting fake news. By this statistical analysis, they revealed that the performance is higher when all profile features are considered than when only explicit or implicit features are considered [6].

B. Text/News content - related approach

A Bengali fake news detection research used two approaches [6]. They used traditional linguistic features such as Lexical features, Syntactical features, Semantic features, and meta-data and punctuation marks frequency. With linguistic features, linear classifiers such as Support Vector Machine (SVM), Logistic Regression (LR), and Random Forest (RF) have been used. As the other approach, they have used Neural Networks based models such as Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM). The evaluation of linear classifiers and neural network-based models has suggested that linear classifiers with traditional linguistic features can perform better than the neural network-based models. To prepare the dataset, they have manually annotated around 8.5k news items. They concluded that, the larger the dataset, the accuracy of the model will be increased [7].

Hussain et. al performed an experimental analysis on the detection of Bangla fake news from social media [7]. In this research work, the authors have used two supervised machine learning classifiers to detect Bengali language fake news with Count Vectorizer and Term Frequency – Inverse Document Frequency Vectorizer as text feature extraction techniques. This approach determines the fakeness based on the article content's polarity. They used two classifiers as, Multinomial Naive Bayes and Support Vector Machine. This research concluded that Support Vector Machine with the linear kernel performs better than Multinomial Naive Bayes on their dataset. For this analysis, they used 2500 articles: real - 1548 and fake - 993 [8].

C. Hybrid approach

In hybrid approaches a combination of the above two types of features have been used such as, text-based features and the user profile-based features. Deokate, S. B's research was done on the fake news on the Internet without restricting only to the social media news. This work used Twitter datasets such as, CREDBANK and PHEME, with rumors in Twitter and BuzzFeed dataset. They used a machine learning classifier which is Support Vector Machine (SVM) to classify news as fake news. The stop words were removed from the text as preprocessing steps, and the features of the text were extracted properly after text feature selection, and the extraction SVM classifier was able to classify data [9]. One text related feature that can be used is, text verifiability against credible sources content. Verifying a news item against credible sources is aligned with the human intuition of assessing a news item's credibility. The psychological aspect of verifying news items with incredible sources, usually done by a human, can be emulated by implementing an automated system for detecting fake news.

A paper proposed an approach for a machine learning-based model for Arabic news credibility assessment. The proposed model consisted of four modules dedicated for Content parsing and features extraction module, **Content Verification Module**, users' comments polarity evaluation module, and credibility classification module. The Decision tree, SVM, and Naive Bayesian (NB) classifier algorithms were used for classification. The results indicated that the performance of the decision tree achieves a higher percentage compared to SVM and NB. In the hybrid approach mentioned above, the authors have used,

- User features (verified? bio and URL availability?)
- Content related features (contains hashtags? user replies' polarity, verified status of text content against credible sources) as the inputs for the classification model [10].

In Al-eidan's research on fake news detection for the Arabic language, they used a hybrid approach that considered the text content and the other features such as similarity with the verified content, lack of inappropriate words, verified status, and an overall degree from a Twitter user grading system. They have normalized the tweet texts for pre-processing steps, removed stop words, performed part of speech (POS) tagging and stem words. Finally, they have represented each document, as a Bag of Words (BOW). They have used BOW with Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer to get a vector representation of the words in the tweet list and documents. They have used two approaches for credibility calculation.

The first approach is used to classify tweets into credibility levels as High credibility, questionable and low credibility based on the text similarity with credibility content only. This work has defined three threshold values according to the POS tags they have used for word tagging. The second approach aims to use other features such as linking, verified status from Twitter to build the credibility formula to calculate the overall score for each tweet. Then they have given each features that are used in the analysis, a weight value depending on the significance of each feature to the overall tweet credibility [11].

The Sinhala language belongs to the Indo-Aryan branch of the Indo-European language family. The Sinhala language writing system is unlike English, where both consonants and vowels are full letters. The complete Sinhala script consists of about 60 letters, with 18 vowels and 42 consonants [12]. Stop-word removal is an important pre-processing step that can be used to remove some common words such as articles, pronouns, prepositions, and determiners [13]. Since stop-words are used in any text, they are considered as unimportant differences between documents. The examples for Sinhala stop-words are the commonly used words such as "ද," "මේ," "ය," "හා," "ඒ," "ම," "ඇත."

After doing a comparable analysis with Indic languages such as Hindi, stop-words in Sinhala sentences also carry vital information about the semantic similarity of a sentence or a word combination. Due to this reason, for some research that use semantic meaning of sentences stop-words are not removed [14]. For English language content, converting listened to listen to reduce the vocabulary, thus reducing the memory requirement can be taken as examples for stemming. Stemming is a technique used to extract the base form of the words by removing affixes from them. For example, the stem of the words මිනිසා, මිනිසුන්, මිනිස්සු are stemmed to 'මිනිස්. For stemming, we used existing already developed 'Sinling' stemming module which is developed for Sinhala language [15].

In another work, authors have used a set of tweet features and allocated points according to their contribution to the overall credibility. Then, they have trained machine-learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM). Regarding credibility classes such as High credible, not credible, etc. the Twitter-only feature based classifier has given a 36% class precision [16].

In the Sri Lankan context, the social media groups or some popular personalities that represent a certain group of people who are having verified social media accounts with a long user account history are also spread misleading or biased information [4]. Therefore, relying only upon the authenticity of user account or source-related features is not sufficient and not appropriate in Sri Lankan context. The use of text content-based approaches may also be constrained because a person cannot identify fake news by simply reading them with naked eyes due to the better imitation techniques of the real news items' characteristics. Considering above limitations, a Hybrid Rule-Based approach for Sinhala Fake News detection is proposed in this research work.

III. METHODOLOGY

The methodology proposed of research work is displayed in Fig. 2. Including all the steps of Data Collection, Data labelling, Feature extraction etc.

A. Data Collection

Twitter news content and user information has extracted using Twitter developer free API. The dataset consisted of tweets that were tweeted from the beginning of the year 2020. Two types of data are used here as:

• Ordinary user tweets
• Tweets collected from credible sources.

First, a list of usernames was prepared from Twitter accounts manually. These usernames list mainly consisted of ordinary user accounts which post tweets in Sinhala. The sources we considered as the credible news sources (8,) which are providing credible information to the society are displayed in TABLE I.

TABLE I. CREDIBLE SOURCES

1	Ada derana sinhala	5	Lankadeepa
2	Mawbima	6	Hiru news
3	RiviraNews	7	SiyathaNewsLive
4	SiluminaLK	8	Siyatha FM

Initially the algorithm to retrieve the tweets, extract the most recent 200 statuses posted by a specified user. Then, the ID of the tweet which is immediately after the extracted oldest

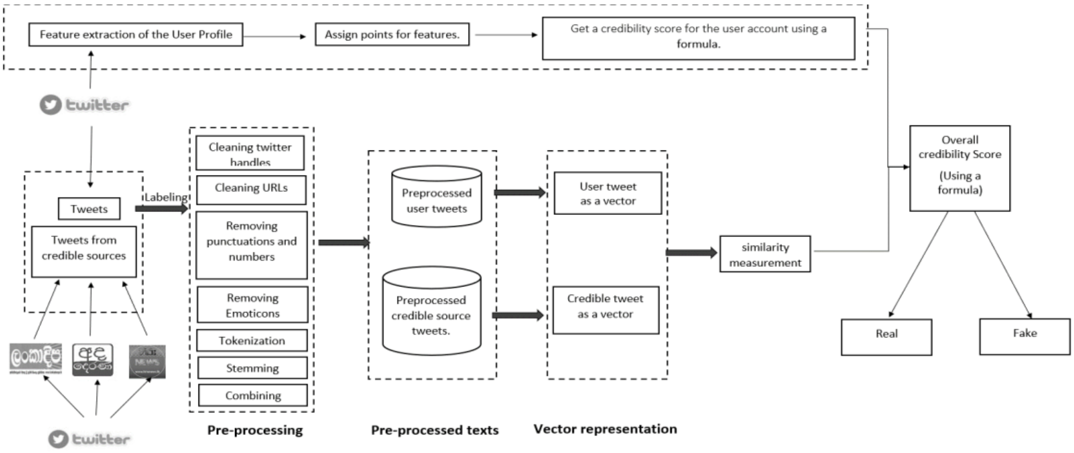

Fig. 2. Proposed Methodology

tweet was saved. Then until there are not any tweets to retrieve (new tweet count is more than zero), the algorithm retrieves the tweets up to an oldest tweet continuously. The data fields (including the user account's attributes) necessary for the analysis were mentioned in the program and after exiting from the loop, new tweets were saved to a CSV file according to the column names that were explicitly mentioned [17].

B. Data Labelling

First, we filtered out the data between 2020/09/01 to 2020/10/30 from both credible and ordinary user tweets. Since the identification of a news item as a fake or real can be differed from person to person with the political and personal views, we had to follow a similar procedure in labelling the tweets. We checked whether a user tweet that we need to label, appears on any of the above sources within a one-week time, if so, we labeled it as real, else as fake. While labelling the outliers in the dataset such as personal messages, jokes, harassing words, and other unnecessary character strings were removed.

Though there was a large user tweet dataset that contains about 20000 tweets, after labelling it reduced to about 164 tweets. There were 80 Fake/misleading tweets and 84 Real tweets that were posted by users. The credible news dataset consisted of about 6300 tweets.

C. Data Preprocessing

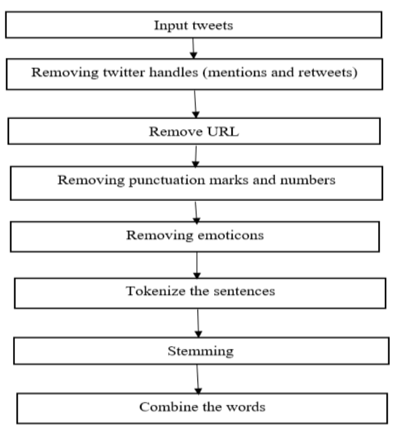

Fig. 3. Preprocessing steps

The collected tweets' text fields needed to be pre-processed before using in any algorithm for similarity detection. In this step, mentions, unnecessary punctuation marks and numbers, non-Sinhala characters, URLs, emoticons, and retweets were removed from the text as in Fig. 3. Since the Sinhala stop words carry a large impact over the sentence's semantic meaning, the stop words were not removed from the tweets.

D. Text Feature Extraction

1) Text Verification Module

Since semantic meaning of a sentence need to be captured for this study, first the text data needs to be converted into a numerical format. Various techniques are available for that, including popular techniques such as BOW, TF-IDF, and Word Embedding models. Since BOW and TF-IDF capture only the frequency or the presence of certain terms but not the semantic meaning of them, considering the need of semantic similarity calculation in this research context word embedding technique for Sinhala language was used. After doing a detailed analysis about existing word embedding techniques for Sinhala, in the initial implementation, we decided to use pre-trained Sinhala FastText models which was developed and trained by Facebook using *Wikipedia* and *CommonCrwal* data.

In FastText, two Vector representation types are available to use as 'getSentenceVector' and 'getWordVector'. After doing an experiment on which performs better, we found out that, getSentenceVector performs better than getting word vectors of a sentence and calculating average of the word vectors to get the sentence vector [18].

The reason for this can be explained as, the Fast Text's generation of Sentence Vector is not just a simple "word average". In pre-trained models (cbow and skipgram) 'getSentenceVector' is generated by dividing each word vector by its norm and then average them. In FastText, 'getSentenceVector 'they have also considered the End of Sentence character (EOS) character when generating vector for entire sentence. Then, the vector similarity of two sentences (ordinary user tweet and credible tweet) were calculated using cosine similarity technique. Cosine similarity can be calculated using spatial module.

From the above approach we expected to get a score for sentence similarity for each tweet with every credible news tweet. If there are 1000 credible source tweets, for each ordinary user tweet, 1000 similarity scores were expected from the above approach. After that, the maximum similarity score gained by each user tweet was recorded to use in further analysis.

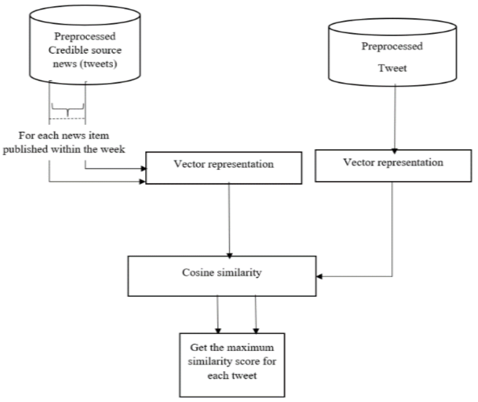

Fig. 4. Text Verification Module Architecture

E. *User Account Feature Extraction*

1) *Defining Rules*

Other than the text verifiability score with credible tweets we also considered the User account features for this hybrid approach. For a given labeled user tweet, we consider the user account features such as, Follower count (FC), Follower Friends ratio (FW), Status Count (SC), Twitter verification status (V), Retweet Count (RT), Favourite_count (FTC), Account Description length (LD), username and screenname equality (SN), location is set(L) and defined rules as in TABLE II to get a score for user accounts.

TABLE II. POINTS SCHEMA

	Feature	Contribution to high level credibility	Points for features
1	FC	If the user account has higher number of followers	10 followers → 1 point
2	FW	If the user account's Followers Count is higher than Friends Count	FW < 1 → 0 point, else 1 point
3	SC	If the user has posted large number of tweets	100 tweets → 1 point
4	V	User account is verified by Twitter	if verified by Twitter → 1 point
5	RT	If the retweet count of a post is higher	1 retweet → 1 point
6	FTC	If the favorite count of a post is a higher	1 favorite → 1 point
7	LD	If the user account description is not empty	if account description is > 0 chars → 1 point
8	SN	If the user account's screen name differs from username	if username is not equal to screen name of the account → 1 point
9	L	If the user account location is not empty	if account location is not empty→ 1 point

2) *Account credibility score calculation*

Then, the credibility score is calculated using the derived credibility formula for a user account as follows:

$$\text{Account Credibility (UC)} = FC+FW+SC+V+RT+FTC+LD+SN+L \quad (1)$$

Then the data normalization is done to take the Account Credibility score in a range of [0,1].

F. *Overall News item credibility assessment*

For each tweet, a credibility score was calculated using the following formula, which is developed considering hybrid features, both user account credibility score (UC) and text content verification/similarity score (TS).

$$\text{Score} = T_{val}\,(UC) + (1 - T_{val})\,TS \quad (2)$$

Where $T_{val} > 0$ decides the relative contributions of similarity calculation and user account credibility to the overall tweet's credibility computation. Since user account credibility plays a subordinate role for overall credibility of the tweets, T_{val} should be a value greater than 0.5, i.e., $T_{val} \in (0.5,1]$. This parameter can be tuned with minimum effort to get a maximum accuracy on the dataset.

TABLE III. EVALUATION

Condition	Status
Score > x	Real/credible
Score <= x	Fake/Not Credible

This overall credibility can be considered as credibility percentage for a tweet. After calculating the score, it will be compared with a threshold value to decide whether it is fake or real. This threshold value can be varied to our need. We can change the threshold value and get different interpretations about the tweet's credibility.

IV. RESULTS AND DISCUSSION

As explained above, Fasttext introduces two possible ways to get vector representations of sentences as 'getWordVector' and 'getSentenceVector'. To compare the performance of two methods an experiment was done on a small dataset. The results are as in TABLE IV. The performance of the getSentenceVector was better than the other. Therefore, in this research work we used 'getSentenceVector' with the original, complete dataset.

TABLE IV. EXPERIMENT RESULTS

	get_word_vectors	get_sentence_vector
Accuracy	0.5036	0.7389
Precision	0.536	0.7224
Recall	0.992	0.8357
F1-Score	0.6692	0.7633

By equation (2), the each of User account Credibility's and Text Verification feature's contribution to the overall news items' credibility can be identified. The value of the T_{val} can be tuned between (0.5, 1] to find out which features holds the higher contribution when the model gives the maximum accuracy. When T_{val} is getting larger, the relative contribution of User account credibility score, to the overall news item's credibility score gets higher. Then the $(1 - T_{val})$ will hold a small value. So that the contribution of text verification to the overall credibility is a lower value as in TABLE V.

In the initial implementation, when the user account features contribution was 0.3, verifiability contribution was 0.7 and the threshold value was given as 0.55; the Accuracy, Precision, Recall and F1-Score was recorded as 77.6%, 80.77%, 78.42% and 79.58%.

TABLE V. RESULTS

Threshold Value = 0.55		
Measures	**T_{val} = 0.3**	**T_{val} = 0.7**
Accuracy	0.7765	0.4493
Macro Precision	0.8077	0.6667
Macro Recall	0.7842	0.0165
Macro F1-Score	0.7958	0.0324

When the user account features contribution is 0.7 and text verifiability contributes by 0.3 the model performance was recorded a lower value. With the above scores when the threshold value was given as 0.55 the accuracy of the model was recorded as 44.9%. The Precision, Recall, and F1-score were calculated and given in the table. From this this process of comparing, it can be concluded that the Text Verification/ Sentence similarity measurement holds a larger contribution to the overall News item's credibility because it gave the highest scores for Accuracy (77.6%) and F1-score (79.58%).

Then, we changed the threshold value with the contribution of Text similarity and found out the accuracies scored in each case. The Table VI shows how the changes in text similarity weight value and threshold value, affect the overall model accuracy.

TABLE VI. TEXT SIMILAIRTY WITH THRESHOLD VALUES

Accuracy Score	**Weight assigned for text similarity**				
threshold value	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**
0.5	0.5599	0.619816	0.730415	0.738894	0.746724
0.55	0.5069	0.541475	0.619816	0.693548	0.776498
0.6	0.4585	0.479263	0.548387	0.59447	0.668203
0.65	0.4516	0.460829	0.465438	0.523041	0.578341

V. CONCLUSIONS AND FUTURE WORK

In this research, we proposed a method to identify Fake News in social media platforms in Sinhala language using a hybrid method, which is a combination of User-Account related features and Text verifiability against credible sources. The hybrid feature methodology was implemented using a Rule based technique. Fake news is an invented form of information or creation of a lie to deceive a group of people. With the upturn in searching social media for news nowadays, misinformation publishing has moved from haphazard situations to organized and systematic efforts. There was a lack of research work done on Sinhala language based fake news detection, so that we had to prepare a dataset that consisted of Sinhala language fake news. To get a score for User account credibility, we used nine rules. Features that were appropriate and influenced credibility of a user account which were identified by literature. In Text verification module, the similarity score was calculated for each user tweet against each credible tweet. Then using another formula, we came up with an overall credibility score for user tweets. Here both user account credibility score's and text verifiability score's contribution were considered. The testing results had an Accuracy of 77.8%, when the Text verifiability score's contribution was higher than the account credibility score's contribution to the overall credibility. The text verifiability against credible sources holds a higher contribution to the overall news item credibility. The reason that, social media companies did not work on detection of Sinhala language fake news is the lack of resources. But with the proposed methodology, we can find a solution by using a smaller dataset. By using a real-time data extraction procedure this approach can be used in Social media platforms to detect fake news real-time.

As future work, an extension to this work can be done using a dataset that also contain English words and Tamil news items. There is fake news type as clickbait which tries to get more visitors to publishers' sites and social media pages using misleading and convincing headlines. But, in most cases, the content of the news item may differ from the headline. These types of fake news can be identified by comparing the headlines and content's semantic meaning.

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