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Credibility Evaluation of User-generated Content using Novel Multinomial Classification Technique

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Abstract—Awareness about the features of the internet, easy access to data using mobile, and affordable data facilities have caused a lot of traffic on the internet. Digitization came with a lot of opportunities and challenges as well. One of the important advantages of digitization is paperless transactions, and transparency in payment, while data privacy, fake news, and cyber-attacks are the evolving challenges. The extensive use of social media networks and e-commerce websites has caused a lot of user-generated information, misinformation, and disinformation on the Internet. The quality of information depends upon various stages (of information) like generation of information, medium of propagation, and consumption of information. Content being user-generated, information needs a quality assessment before consumption. The loss of information is also necessary to be examined by applying the machine learning approach as the volume of content is extremely huge. This research work focuses on novel multinomial classification (based on multinoulli distribution) techniques to determine the quality of the information in the given content. To evaluate the information content a single algorithm with some processing is not sufficient and various approaches are necessary to evaluate the quality of content. We propose a novel approach to calculate the bias, for which the Machine Learning model will be fitted appropriately to classify the content correctly. As an empirical study, rotten tomatoes' movie review data set is used to apply the classification techniques. The accuracy of the system is evaluated using the ROC curve, confusion matrix, and MAP.

Keywords: Digitization, Multinomial Classification Technique, Transform communication etc.

I. Introduction

In the year 2022 alone, 4.8 billion people used social media or the likewise platforms. Most users used mobile phones for creating and using digital information in various forms (PutriGhaisani et al., 2018). If the volume of users either creating or consuming the content is very high, it is difficult to monitor the quality of the content. Trust in the content is possible if the author of the content is known (Boukhari&Gayakwad, 2019). The evaluation of the quality is necessary when there is no previous history available about the author and the consumer does not know the author directly. In this case, the manual or automated approach to deciding the quality of content is extremely necessary. The existing social networking websites let the authors write the content first and later the content which is not aligned with the societal norms is removed (Kaliyar et al., 2021). The evaluation of content requires a thorough investigation or a machine learning technique for the content. Considering the large volume of data, the machine learning approach obviously proves to be a more suitable choice. In the area of machine learning, there are several classification and regression algorithms. Out of these, based on the related relevant literature, Support Vector Machine (SVM) and Logistic Regression (LR) are common algorithms reported to perform better compared to others (Verma et al., 2021). The reason for using multi-category classification is to minimize the scope of evaluating the quality of content in the form of true or false only (Zheng & Qu, 2020).

The rest of the paper is organized as follows. Section 2 of the paper presents a comprehensive review of the related literature while a detailed description of the methodology is presented in section 3. This is followed by results and discussion in section 4, followed by the concluding remarks and description of future work in section 5.

II. Literature Survey

Information is manipulated in various forms like misinformation, and disinformation. Misinformation deals with false information irrespective of the motive behind this type of information generation. Disinformation is deliberately generated information to misguide people. Fake news is, hence, a category of one types of misinformation or

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disinformation(Gayakwad & Patil, 2021). Correct and quality information is missing in all these forms of information. The issue of fake news is not recent. It has just gained momentum with the digitalization and popularity of social networking websites. An excellent example, to prove the potential of how misinformation or disinformation could mislead people, is the case of the US election in 2016 (Gehrau et al., 2021). In the COVID-19 pandemic, people also misused the data associated with COVID-19. To avoid this type of misuse of information, correctness must be guaranteed(Maurya Maruti and Gayakwad, 2020). A lot of studies have been carried out on fake news detection and information credibility. There are various dimensions and factors involved as per the applicability. User-generated information, user profile, platform, propagation, and consumption are the key components to evaluating the quality of information (Zhou et al., 2021). Various models are dealing with fake news detection or any information credibility. Some of the models are based on Natural Language Processing (NLP), surveys (including the investigation of the content), and machine learning techniques. Depending upon the application of credibility of information the respective model is selected. Also, in recent years, BERT and GPT 2 have been important in dealing with unlabelled data (Mahmood et al., 2019). Further, Convolution Neural Network (CNN) has been used to decide the correctness of the information, in recent times(Silva-Palacios et al., 2017). An LSTM-based approach is also utilized in memorizing true and false information(Jha et al., 2019). One of the major challenges in fake news detection systems is the lack of unlabelled data. Either data must be generated by using an Application Programming Interface (API) like Beautiful Soup with simple web scraping or the researcher needs to rely on the existing data (Hu et al., 2020).

Table 1. Comparative Analysis

Approach	*Use*	*Limitations*
K-Class SVM	Fast because of the sparsity	Output is in the form of a number instead of the probability
K-Class Logistic regression	Useful in non-linear separation, Regularization is available	Useful for Binomial Distribution
Decision Tree	Useful for Hierarchical data	Susceptible to overfitting
Multiclass Perceptron	Based on Multilayer Perceptron, Useful in structural and Hierarchical datasets	Rigid minima cause undertraining
Random Forest	Useful in more number classes, Time-efficient	Overtraining is possible because of a lack of regularization
Multinomial Classification	Useful in avoiding the overfitting using the weighted sum and error	Higher values of error may result into undertraining
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Believability is an individual's perception and there is no specific benchmarking to decide the quality of content (Cai et al., 2020; Shah et al., 2020). The same piece of information can be mentioned in diverse ways, depending upon the expertise, perception, and target user (Li, 2020) . A user creates content, the user consumes the content, and it is a user who determines the quality of the content (Tully et al., 2020). There are various approaches proposed by the researchers for deciding the credibility of the information. To name a few of them, such approaches include classifications algorithm, regression algorithm, survey, and hybrid classification (Flanagin et al., 2020). The researchers have tried to implement these approaches on different datasets. A direct comparison or comment on the accuracy is difficult to make, as these approaches are not on the common ground (Gayakwad, 2020). Still, the common observation is about the accuracy which is better in the combined approaches rather than relying on a single algorithm or a single approach (Purba et al., 2021). Dataset collection also differs as the approach changes (Blondeel & Bb, 2015), for example, the dataset for analyzing the credibility of the posts on social media is different than the credibility assessment of a normal article published on a website (Gayakwad & Patil, 2021). The modeling of the approach changes according to the dataset, the loosely coupled approach is difficult because a lot of pre-processing is needed before proceeding with the training and testing of data . As the data type, percentage of the missing values, and encoding change the entire feature selection process changes(Beldar et al., 2016).

The approaches used for multinomial classification are K-SVM, K- Logistic Regression, and Multiclass perceptron and Decision Tree (DT) . These approaches are based on the ‘One

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versus One' or 'One versus All' phenomenon. The term multinomial is applicable for the specialized type of categorization which follows the typical Multinoulli distribution. The Multinoulli distribution, in turn, is a form of multivariate distribution based on the well-known Bernoulli's distribution (Kakol et al., 2017). The comparison of the existing models based on the thorough review of pertinent literature is presented in tabular format through Table I. This comparison provides insights into the existing multinomial classification techniques, their uses, and their limitations.

Individuals and groups employ mobile and web-based technology to construct highly interactive platforms where they may share, co-create, discuss, and alter user-generated content

Transform communication between corporations, organizations, communities, and individuals in a significant and widespread way (ICMLSC 2022: 2022 The 6th International Conference on Machine Learning and Soft Computing, 2022). Users of social media platforms, as opposed to traditional media outlets, become content creators rather than content evaluators. In our daily lives, we come across a lot of information, and one of the characteristics we use to evaluate it is its trustworthiness, or believability (Aggarwal, 2022). Information credibility is described as one's perception of how trustworthy information is , and it is a powerful predictor of an information consumer's subsequent actions (Yao et al., 2022). Because large-scale collaborative creation is one of the keyways in which information is formed in the social network, user-generated material is sometimes viewed with suspicion; readers do not regard it as a reliable source of information. Previous research has revealed how to assess the reliability of the information in traditional media or on the internet. However, there aren't enough professional gatekeepers to regulate content on social media networks(Chang & Peng, 2022). The research in (Pande et al., 2022, Pande et al., 2020, andPande et al., 2020) provides insights for the problems present in comparable domains. It's not uncommon for unsubstantiated or false information to continue to circulate on social media. Information consumers are obliged to hunt for new techniques to evaluate genuine information in this environment. While some academics have investigated concerns of information reliability on social media, they have mostly focused on one sort of platforms, such as blogs or Twitter. Furthermore, many past research findings were fragmented and ambiguous. Our comprehension of the topic has been constrained due to the fragmented condition of study and the lack of a unified theoretical underpinning the components of social media platform credibility assessment as a result, the topic of what factors determine the reliability of the information on social media platforms remains unanswered.

III. Methodologies

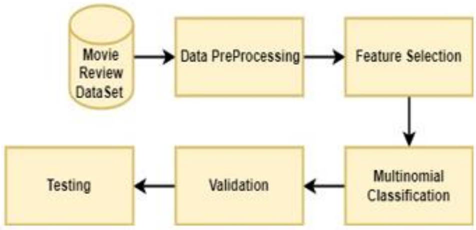

Fig. 1: Multinomial Classification

Dataset: The movie review data set of Rotten Tomatoes1 available on Kaggle is used for the experimentation. The data is fetched from Kaggle to the Google Collab platform in the form of a Comma Separated Values (CSV) file. The data was not found in a format that could be used directly for performing the experimentation and therefore was subjected to pre-processing.

Data Pre-processing: Data pre-processing contained various steps like missing value analysis, removal of impurities, null value analysis, and understanding the format of information (for various features). The interpolation technique was used to identify the probable value at the place of Null or NaN values. Table II presents the selected features, following the correlation and backward selection method. The scaling of the data is available in various formats like a number, grade, etc. One of the prominent features of this dataset was the review content. It was to vectorization of words in the content. The evaluation of content is performed by converting words into normalized numbers using the NTLK library.

Feature Selection: Features were selected based on the heat map of correlation amongst the features. Moreover, the backward selection technique was used to remove the least relevant features.

Multinomial Classification: Multinomial classification is a model which combines the best performing classification algorithms like Support Vector Machines (SVM), Naïve Bayes (NB), and Logistic Regression (LR). The uniqueness of this method lies in identifying the bias value to be added along with the combination of these three algorithms. This bias balances the model by avoiding the overfitting of the model.

Validation: To evaluate the performance of the multinomial classification model ROC, MAP, and confusion matrix were used. The novel multinomial classification model delivered an accuracy of 95.22%.

Testing: Model testing was performed by applying 70:30 split of the data set for training and testing. The performance of the

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proposed model was also evaluated by comparison with the existing classification algorithms on the same data set.

[1]https://www.kaggle.com/datasets/stefanoleone992/rotten-tomatoes-movies-and-critic-reviews-dataset

IV. Results and Findings

Validation of multinomial classification model was performed by calculating the micro average for classes two precision-recall curves, multinomial classifier for content modeling, arrow seeker, arrow seeker with an area, precision-recall curve, confusion matrix before and after normalization. As depicted in Fig. 2, the curve is plotted with an average precision of 0.53. This indicates the balance between precision and recall during the classification. The micro-average for the classes is plotted with a scale of 0.2 - 1.0.

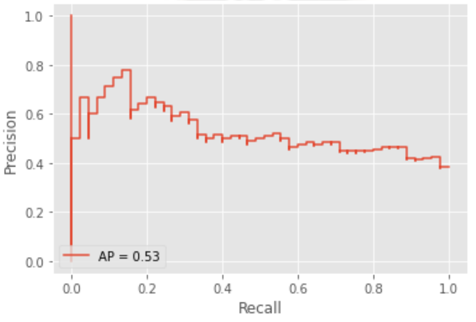

Fig. 2: Micro Average for the classes

The graph of the precision level at positive label one is plotted against the recall add positive label 1. The result of two class precision-recall curves can be seen in Fig. 3. The accuracy of the multinomial classification model is 0.95.

Table 2. Feature Selection Overview

Sr. No.	***Feature***	***Feature Type***	***Missing***
1	Date	X	0
2	Review Type	X	18559
3	Top Critique	X	0
4	Review Context	X	65805
5	Review Score	Y	0

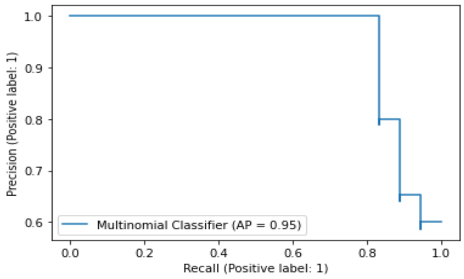

Fig. 3: 2-class Precision-Recall curve

To understand the extent of accuracy the graph of the true positive rate is plotted against the false positive rate which also covers the area under the ROC curve which is equal to 0.82 (as shown in Fig. 4). Fig. 5 indicates that the coverage of an area is further improved by applying the buyers. The area under the curve is now 0.9949. The area covered by the curve indicates the associated true positive rate and false-positive rate.

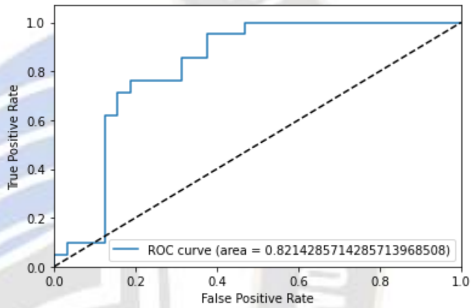

Fig. 4: ROC curve

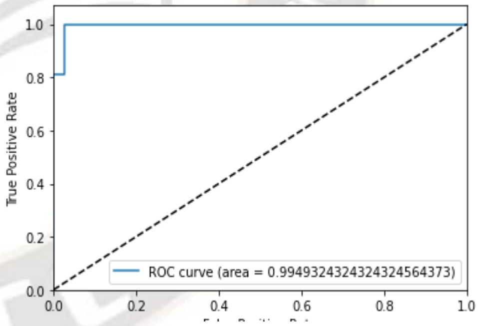

Fig. 5: ROC curve – area

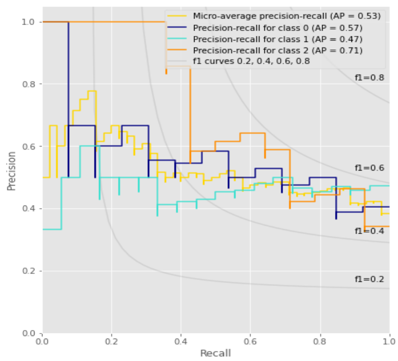

Fig. 6: ROC curve of all classes

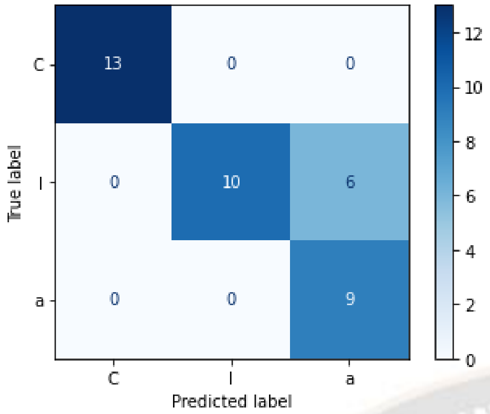

Fig. 7: Confusion Matrix before normalization

Fig. 6 indicates the summarized analysis of the multinomial classification model, micro average precision-recall, precision-recall for various classes, and F1 curve. It also presents the plotting for different values of F1 like 0.2, 0.4, 0.6, and 0.8 in the graph. Also, the graph indicates the curve with the minimum value point at the curve. Notably, the curvature is sharper at F1=0.2.

Fig. 7 presents the association between the predicted and actual values plotted on a scale of 1-14. Higher values can be seen diagonally from the bottom right to the top left. The highest value can be noted to be 13. All these values are before the normalization was performed.

Fig. 8 indicates the confusion matrix from 0–1, the values are higher at ‘ca’, ‘ac’, ‘II’, and ‘Ia’. This indicates that the more useful values are fetched after using the normalization.

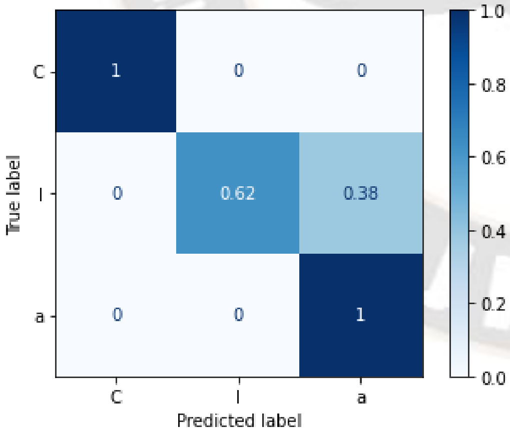

Fig. 8: Confusion Matrix after normalization

The Multinomial classification is designed to classify the data where there is non-binary (i.e. multi-category) output. Also based on the type of the class structure, the hierarchical or generic method is used. The classification requires several iterations to classify the data appropriately. The overtraining may result in not categorizing the data correctly. The regularization parameter avoids overfitting up to a certain extent, but the minima of the convex curve are not assured. Also, there is a least botheration with loss of the information.

The proposed novel multinomial model classifies the data using the ensemble approach where the LR algorithm is used along with multiclass SVM. The weight for which the model delivers the optimum performance is calculated and thereafter the weighted average of the classifiers is used, unlike conventional stacking, bagging, and boosting. Moreover, the bias is added, which is the square of weighted sum and error. This ensures less loss of information, fewer errors, and more precise categorization as indicated in the graphs.

V. Conclusion and Future Work

The empirical study of deciding the credibility of content using a multinomial classification model is performed on a movie review data set. The results of the experiments indicate that the model could be implemented successfully as it categorized the credible reviews from the data set. ROC and precision-recall values also support the accuracy of the model. Confusion matrices demonstrate that the relationship amongst the algorithms is improvised after using normalization. Thus, the novel multinomial classification model performs better for the movie review data set. Though the reported results are for the dataset considered for experimentation, we advocate that the proposed model could be applied with similar efficiency for the datasets of other domains as well. In the future, along with the categorization, we will be considering the extent of membership for deciding the credibility of the content. Also, we will consider the evaluation of the percentage of loss of information.

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