FAKE NEWS DETECTION ON KAGGLE DATASETS USING DECISION TREE ALGORITHM

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ABSTRACT

Today, social media is widely used to disseminate real-time news. Users of social media are scattered over a wide range of people and do not belong to any one age or gender category. This is due to the fact that it is simple to transmit, spreads quickly, is simple to access, and costs little to spread the word. Social media users are utilising it to disseminate fake news, and malicious information for purposes of commerce, politics, and entertainment. This dissertation offered four approaches to use in judging the veracity of the news, so limiting its dissemination, to address these challenges. The sharing of information via the internet has been increasing over the years. The internet has been a source of easy information and is used more than traditional ways like newspapers or magazines. It is important to identify information from the internet as real or fake as misleading information could cause a lot of havoc in society. Fake information can be the cause of riots, and chaos and can affect a large group of society. In this paper, the methodology used to detect false news using machine learning classifiers to authenticate whether the news is real or not. For the generation of feature vectors, TF-IDF Vectorizer have been utilized. To detect the news as fake or real , the proposed approach is compared with several

Keywords: - Fake news detection, logistic regression, decision tree, random forest, gradient boosting, TF-IDF Vectorizer, Machine learning.

1.INTRODUCTION

After the middle of the 1990s, the World Wide Web underwent a significant development, and online social media began to be used for interpersonal communication. The majority of people use social media platforms to communicate opinions, and they come from a variety of ages, genders, and communities, according to research by Jiang et al. [1]. Users

utilise Twitter and Facebook, two software behemoths in the social media space, to share real-time news. Due to their rapid information sharing, low cost, and ease of use, social media platforms are now regarded as key platforms.Videos, photos, or text that is sent to spread false information with false facts is referred to as fake news. Even though the news may appear to be true at first, it will elicit surprising responses and draw readers'attention. They are made by organisations or people who are driven by their own interests, which could be driven by personal, political, or economic agendas. With the advent of print media, bogus news

has been widely disseminated. But because of the digital exchange, they are becoming prevalent and common. Fake news is more visible in a shorter period of time because social media sharing is simple and quick.

2. RELATED WORKS

The main focus of Georgios et alstudy .'s article [5] is the identification of bogus news. The author chose machine learning methods to solve the problem and employed the content-based feature to produce accurate findings. With the help of the author's experiments, it was simple to identify between phoney and authentic news. The investigation began with a thorough feature analysis of the data. The author decided to use a variety of machine learning techniques and ensemble

algorithms, which are quite effective at handling text classification tasks, to detect fake news in written narratives and word embeddings. AdaBoost, SVM, DT, Bagging, and other algorithms were utilised by the author, who also decided to undertake tests using obsolete data sources. The goal of the study work by Cody et al. [3] is to automatically detect false information in Twitter discussions. The author devised the automatic detection method after looking into the CREDBANK and PHEME accuracy assessment processes. The author conducted experiments using three datasets: PHEME, a prospective rumours dataset with journalists' accuracy assessments; CREDBANK, a crowdsourced dataset of accuracy evaluation; and BuzzFeed's false news dataset. The author initially found certain features falling under four kinds, aligned the three datasets in a consistent way, employed classifiers, and then analysed each feature set under the receiver operating characteristic (ROC)curve to construct the model for detection.

Judee et al. [8] idea of making use of linguistic traits as instruments to identify dishonesty in communication established the groundwork for this study paper. The author first chose two tests for the research: surviving in the desert and flying. Nonetheless, the outcomes of these two tests were inconsistent. As a result, the author chose to conduct in-depth research on a theft scenario. Results were analysed using both individual and cluster cues. Data mining algorithms were employed for cluster analysis, which assisted the author in creating an automatic criteria for spotting fraud. The author used C4.5 [1], which eliminated unnecessary branches and limited error rates.

According to Zubair et al. [6], misleading news can be filtered or classified using machine learning techniques including SVM, RF, NB, and DT. For this, the author selected a few sets of both fake and real news stories. On the basis of the texts of the news stories he has chosen, the author attempts to construct a classification strategy. The aforementioned classifiers were applied to AdaBoost and Bagging during the classification process. With the help of Pycharm in the Python environment, these tests were run. Classification parameters like recall, ROC, F-score, accuracy, and precision were used to gauge the classifier's performance. All of these examinations of the news have taught the author how to identify fake news and locate its source. The top-performing classifiers were determined by comparing the classification metrics

ofseveral classifiers. In order to combat fake news, which poses a serious threat to several sectors, Rohit et al. [10] propose a deep convolutional neural network called the Futue Network Development. Instead of depending on manually created characteristics, the author would like to create a model that uses numerous hidden layers in a deep neural network to automatically learn various discriminatory features for the categorization of fake news. At each layer, the CNN will assist in extracting features whose performance may he evaluated against benchmark models. Tao Jiang [11] hold-out

cross-validation was used to evaluate how well three deep learning models and five machine learning models performed on two fake and real news datasets of varied sizes. The models' performance was evaluated using accuracy, precision, recall, and F1-score, and a modified version of McNemar's test was used to determine whether there was a significant difference. Then, we showed our unique stacking model, which, when applied to the ISOT dataset and the KDnugget dataset, respectively, achieve, a testing accuracy of 99.94% and 96.05%. In addition, our proposed approach outperforms conventional methods.

3. PROPOSED SYSTEM DESIGN

The proposed system classifies new articles as true or false based on the currently available data when presented with a scenario of a group of news items. This forecast is based on how the terms used in the article relate to one another. By employing a Word2Vec model to identify the links between words, the suggested method can categorize new articles into those that are true and those that are false.

Datasets are used to hold input that is gathered from a variety of sources, including newspapers and social media. Datasets will be used as input by the system. The datasets go through preprocessing, when the extraneous data is deleted and, if necessary, the data types of the columns are altered. In the preceding phase, Google Collab is utilized. Dataset is used to train the machine for fake news detection. The entire dataset is split into two datasets before commencing the false news identification phase. 20% is used for testing, while the remaining 80% is for training. The model is trained using the training dataset by machine learning algorithms. The test dataset is used as the input, and a projected result is produced. To determine the number of accurate and incorrect predictions in the context of true and false news, the predicted and actual outputs are compared.



FIGURE1- PROPOSED SYSTEM DESIGN

TIJER || ISSN 2349-9249 || © February 2024, Volume 11, Issue 2 || www.tijer.org 4. IMPLEMENTATION 5.PERFORMANCE METRICS Importing Required Library Definition

from google.colab import drive drive.mount('/content/drive') import pandas as pd import numpy as np import seaborn as sns import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.metrics import accuracy_score from sklearn.metrics import classification_report import import string

Inserting Fake And Real DataSet

df_fake=

pd.read_csv("/content/drive/MyDrive/Fake.csv.zip")

df_true=

pd.read_csv("/content/drive/MyDrive/True.csv.zip")

df_fake.head(5)

df_true.head(5)

Inserting a column called "class" for fake and real news dataset to categoriesfake and true news.

 $df_fake["class"] = 0$

df_true["class"] = 1

Removing last 10 rows from both the dataset, for manual testing

df_fake.shape, df_fake_manual_testing = df_fake.tail(10) for i inrange(23480,23470,-1):

df_fake.drop([i], axis = 0, inplace = True) df_true_manual_testing = df_true.tail(10) for i inrange(21416,21406,-1):

df_true.drop([i], axis = 0, inplace = True) df_fake.shape, df_true.shape

Merging the manual testing dataframe in single dataset and save it in a CSV file

df_fake_manual_testing["class"] = 0 df_true_manual_testing["class"]=1 df_fake_manual_testing.head(10)

df true manual testing.head(10)

Merging the main fake and true dataframe

df_marge = pd.concat([df_fake, df_true], axis =0) df_marge.head(10)

df_marge.columns

Performance metrics are important in evaluating the effectiveness of any machine learning algorithm, including decision tree algorithms used for fake news detection. The following are some performance metrics that can be used in evaluating the effectiveness of decision tree algorithm for fake news detection:

Accuracy

This measures the proportion of correct classifications to total classifications made by the decision tree model. A higher accuracy indicates that the model is performing well in distinguishing between fake and real news.

Accuracy =
$$\frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \longrightarrow 1$$

Precision

This measures the proportion of true positives to the total number of positive classifications. A higher precision indicates that the model is able to accurately identify fake news.

$$Precision = \frac{TP}{TP + FP}. \longrightarrow 2$$

Recall



This measures the proportion of true positives to the total number of actual positives. A higher recall indicates that the model is able to identify more of the fake news present in the dataset.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \longrightarrow 3$$

F1-Score

This is the harmonic mean of precision and recall, and provides a combined metric of the two. A higher F1 score indicates that the model is able to achieve high precision and recall

$$F1 - score = 2 \frac{Precision \times Recall}{Precision + Recall} \longrightarrow 4$$

6.SCREENSHOTS

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4						c	D	
1 title			text	0	subi	iert	date	
2 Donald True	o Sends Out Embarr	assing New Year's Fee Message	Donald Trump just couldr	t wish all Americans a Har	nov New Year and leav New	VE	31-Dec-17	
3 Drunk Braes	ng Trumn Staffer Sta	rted Russian Collusion Investig	ti House Intelligence Comm	ittee Chairman Devin Nune	es is going to have a h: New		31-Dec-17	
4 Sheriff Davis	Clarke Becomes An	Internet Joke For Threatening	In On Friday, it was revealed	that former Milwaukee St	periff David Clarke wh New	vs	30-Dec-17	
Trump Is So	Obsessed He Even Ha	as Obama's Name Coded Into H	is On Christmas day, Donale	Trump announced that he	would be back to wo New	vs	29-Dec-17	
Pope Franci	Just Called Out Don	ald Trump During His Christmas	S Pope Francis used his ann	ual Christmas Day message	e to rebuke Donald Tri Nev	vs	25-Dec-17	
Racist Alaba	ma Cons Brutalize Bl	ack Boy While He Is In Handcuf	fs The number of cases of c	ons brutalizing and killing p	eople of color seems New	vs	25-Dec-17	
Fresh Off Th	e Golf Course. Trump	Lashes Out At FBI Deputy Dire	ct Donald Trump spent a go	od portion of his day at his	solf club, marking the New	vs	23-Dec-17	
Trumo Said	ome INSANELY Raci	st Stuff Inside The Oval Office	Ar in the wake of yet anothe	er court decision that derail	led Donald Trump s pli New	vs.	23-Dec-17	
Former CIA	Director Slams Trump	Over UN Bullving, Openly Suga	e Many people have raised	the alarm regarding the fai	ct that Donald Trump New	vs	22-Dec-17	
WATCH: Bra	nd-New Pro-Trump	d Features So Much A** Kissin	g Uust when you might have	thought we diget a break	from watching people New	vs	21-Dec-17	
Papa John's	Founder Retires, Figu	res Out Racism Is Bad For Busin	e A centerpiece of Donald	Trump s campaign, and nov	v his presidency, has b New	vs	21-Dec-17	
WATCH: Par	Ryan Just Told Us H	le Doesn't Care About Strugglin	Republicans are working	overtime trying to sell their	scam of a tax bill to t New	vs	21-Dec-17	
Bad News F	or Trump - Mitch M	Connell Says No To Repealing	O Republicans have had sev	en years to come up with a	a viable replacement f Nev	vs	21-Dec-17	
WATCH: Lin	lsey Graham Trashes	Media For Portraying Trump A	s 'The media has been talki	ng all day about Trump and	the Republican Party New	VS	20-Dec-17	
Heiress To D	isney Empire Knows	GOP Scammed Us - SHREDS Th	er Abigail Disney is an heires	s with brass ovaries who w	ill profit from the GOI New	vs	20-Dec-17	
Tone Deaf 1	rump: Congrats Rep.	Scalise On Losing Weight After	Y-Donald Trump just signed	the GOP tax scam into law	. Of course, that meai New	vs	20-Dec-17	
The Internet	Brutally Mocks Disn	ey's New Trump Robot At Hall O	of A new animatronic figure	in the Hall of Presidents at	Walt Disney World w New	vs	19-Dec-17	
9 Mueller Spo	esman Just F-cked U	Ip Donald Trump's Christmas	Trump supporters and the	e so-called president s favo	rite network are lashi New	VS	17-Dec-17	
SNL Hilariou	sly Mocks Accused C	hild Molester Roy Moore For Lo	as Right now, the whole wo	rld is looking at the shockin	g fact that Democrat New	vs	17-Dec-17	
1 Republican!	enator Gets Dragged	For Going After Robert Muelle	r Senate Majority Whip Joh	nn Cornyn (R-TX) thought it	would be a good idea New	vs	16-Dec-17	
2 In A Heartle	s Rebuke To Victims	Trump Invites NRA To Xmas Pa	art It almost seems like Dona	ald Trump is trolling America	a at this point. In the I New	vs	16-Dec-17	
KY GOP Stat	Rep. Commits Suici	de Over Allegations He Moleste	d In this #METOO moment,	many powerful men are be	eing toppled. It spans New	vs	13-Dec-17	
Meghan Mc	ain Tweets The Mos	t AMAZING Response To Doug	Jc As a Democrat won a Ser	ate seat in deep-red Alaba	ma, social media offe New	vs	12-Dec-17	
CNN CALLS	T: A Democrat Will R	epresent Alabama In The Senal	te Alabama is a notoriously	deep red state. It s a place	where Democrats alv. New	VS.	12-Dec-17	
White Hous	: It Wasn't Sexist For	r Trump To Slut-Shame Sen. Kirs	t A backlash ensued after (Donald Trump launched a se	exist rant against Kirst Nev	vs	12-Dec-17	
7 Despicable	rump Suggests Fema	le Senator Would 'Do Anything'	V Donald Trump is afraid of	strong, powerful women.	He is a horrific misogy New	vs	12-Dec-17	
8 Accused Chi	d Molesting Senate (Candidate Roy Moore Sides Wit	h Ronald Reagan is largely	seen as the Messiah of the	Republican Party. Des Nev	vs	11-Dec-17	
WATCH: For	Host Calls For A 'Cle	ansing' Of The FBI, And To Arre	st Judge Jeanine Pirro has	continued her screamy rage	ey meltdown over spe New	vs	10-Dec-17	
0 Liberal Grou	p Trolls Trump At Ro	Moore Rally In The Best Possi	bl Donald Trump held a rally	for Alabama Senate candi	date and alleged pedo Nev	vs	9-Dec-17	
Liberaroro	p mois multip Ac No	y moore naity in the best Possi	or burialu trump nelu a ranj	nor wabarna senate canor	care and aneged beacher	1 1221	9-Dec-11	

FIGURE 6.1-DATA COLLECTION

News from six distinct industries are included in the Fake News Database dataset: technology, business, education, sports, politics, and entertainment. The dataset's real news was gathered from numerous popular news websites, primarily in the US, including ABC News, CNN, USA Today, New York Times, Fox News, Bloomberg, and CNET, among others.

1. L	ogistic I	Regi	ression					
[28]	from skl	earn.	linear_mode	l import l	.ogisticReg	ression		
[29]	LR = Log LR.fit(x	istio v_tra	Regression())				
	Logistic	Regre	ession()					
[30]	pred_lr=	LR.pr	redict(xv_te	st)				
[31]	LR.score	(xv_t	est, y_test)				
	0.986274	50980	39216					
[32]	<pre>print(cl</pre>	assit	fication_repo	ort(y_test	, pred_lr))		
			precision	recall	f1-score	support		
		0	0.99	0.98	0.99	5849		
		1	0.98	0.99	0.99	5371		
	accu	racv			0,99	11220		
	macro	avg	0.99	0.99	0.99	11220		
	weighted	avg	0.99	0.99	0.99	11220		

If the outcome variable only has two possible values, the model is referred to as a binary logistic regression model.

Both real news (Y = 1) and fraudulent news (Y = 0) are possible in this situation. The chance that a record belongs to a positive class when Y = 1 is represented by P (Y=1) = ez/(1 + (ez)) in the binary logistic regression model.Based on previous data set observations, the logistic regression statistical analysis technique can be used to predict a binary result, such as yes or no (binary classification). A supervised statistical method is used to determine the likelihood of the dependent variable.

[33] f	rom sklearn.	tree import	DecisionT	reeClassif	ier		
[34] C	OT = Decision OT.fit(xv_tra	TreeClassifi in, y_train)	er()				
D	ecisionTreeC	lassifier()					
[35] p	red_dt = DT.	predict(xv_t	est)				
[36] 0	T.score(xv_t	est, y_test)					
0	.99607843137	2549					
[37] p	rint(classif	ication_repo	rt(y_test	, pred_dt))		
		precision	recall	f1-score	support		
	0	1.00	1.00	1.00	5849		
	1	1.00	0.99	1.00	5371		
	accuracy			1.00	11220		
	macro avg	1.00	1.00	1.00	11220		
La!	eighted avg	1.00	1.00	1.00	11220		

Combining gradient descent and boost is known as gradient boosting. For each successive model in gradient boosting, the loss function from the preceding model is scaled down using the gradient descent method. By repeating this process, the estimation of the target variable is improved.

2 Cradiant D-	acting Ol-	alfiar				
3. Gradient Bo	osting Clas	sitier				
[38] from sklear	n.ensemble im	nport Grad	lientBoost	ingClassifier		
[39] GBC = Gradi	entBoostingCl	assifier(random st	ate=0)		
GBC.fit(xv_	train, y_trai	in)	- unuon			
GradientBoo	stingClassifi	er(random	_state=0)			
[40] pred_gbc = 0	SBC.predict(>	v_test)				
[41] GPC score/y	tost v tos	+)				
[#1] Obc.score(x	_cesc, y_ces	, , ,				
0.995632798	573975					
[42] print(class	ification_rep	port(y_tes	t, pred_g	bc))		
	nrecision	recall	f1-score	e support		
	precision	recall	11-scori	support		
	0.99 1.00	0.99	1.0	0 5849 0 5371		
accuracy	/		1.0	0 11220		
macro av	g 1.00	1.00	1.0	0 11220		
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4. Random For	est Classifie	er			E.	3
4. Random For [43] from sklearn	est Classifie .ensemble impo	er ort RandomF	ForestClass	sifier	ç	3
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 4. Random For [43] from sklearn [44] RFC = Random RFC.fit(xv_t 	est Classifie .ensemble impo ForestClassifi rain, y_train;	er ort RandomF ier(random_)	ForestClass _state=0)	sifier	C	1
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4. Random For [43] from sklearn [44] RFC = Random RFC.fit(xv_t RandomForest [45] pred_rfc = R [46] RFC.score(xv 0.9905525846	est Classifie .ensemble impo Forestclassifi rain, y_train, classifier(rar FC.predict(xv, _test, y_test; 702318	er ort RandomF ier(random_ indom_state= _test))	ForestClass _state=0) .0)	sifier	č	
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A method that lowers the variance of an estimated function of prediction is known as bagging or bootstrap aggregation. Bagging functions effectively with high variance and low-bias categorization algorithms like trees. As a notable advancement in bagging, random forests represent a considerable group. Take an average for the associated trees after that. With no increase in variance, Random Forest improved on bagging by reducing correlation across trees. Since they are easier to train and tune, random forest performance often resembles that of boosting.

8. REFERENCES

Random forests are hence popular algorithms that are used with different packages

7. CONCLUSION AND FUTURE WORK

As a result, the model uses modules to deal directly with cleaned data. Additionally, algorithms were used to train the data. Manually classifying news demands in-depth subject knowledge and the ability to spot irregularities in the content. Using ensemble methods and machine learning models, we examined the problem of categorising bogus news items in this study. Instead of expressly classifying political news, the data we used in our study was compiled from news articles from a number of domains that cover the majority of e-news. The basic goal of the search is to identify textual patterns that discriminate between false and legitimate news. The learning models were trained and parameterized to attain the highest level of accuracy. Compared to other models, some have attained a better level of accuracy. To evaluate the effectiveness of each method, we used a variety of performance indicators. Comparing the resemble learners to the individual students, the resemble learners have often performed better. Researchers need to focus on several open problems in fake news identification. Machine learning algorithms can be used to identify the primary sources engaged in the dissemination of fake news, for example, to decrease the spread of fake news, identifying key factors involved in the spread of news is an important first step .Put the classifiers together to improve performance. Check the news's sources. Search the news online to examine the news content, on the one hand, warning news consumers and promoting tools so they can be informed and question the sources of information is a very positive thing, but on the other hand, we might be creating news consumers who don't believe in the value of well-sourced news and distrust everything. The latter course could lead to a general condition of confusion where news consumers are indifferent or unable to judge the reliability of any news source.

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