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A COMPARATIVE STUDY OF FAKE JOB POSTS USING DIFFERENT DATA MINING TECHNIQUES

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ABSTRACT

In recent years, due to advancement in modern technology and social communication, advertising new job posts has become very common issue in the present world. So, fake job posting prediction task is going to be a great concern for all. Like many other classification tasks, fake job posing prediction leaves a lot of challenges to face. This paper proposed to use different data mining techniques and classification algorithm like Logistic Regression, support vector machine, naive bayes classifier, random forest classifier, to predict ajob post if it is real or fraudulent. Our application was built which takes Job Id, Description and job Requirements to predict whether the given job post is real or fake. We have experimented on Employment Scam Aegean Dataset (EMSCAD) containing 18000 samples. The trained classifier shows approximately 98% classification accuracy to predicts fraudulent job post

1. INTRODUCTION

In modern time, the development in the field of industry and technology has opened a huge opportunity for new and diverse jobs for the job seekers. With the help of the advertisements of these job offers ,job seekers find out their options depending on their time, qualification, experience, suitability etc. Recruitment process is now influenced by the power of internet and social media. Since the successful completion of a recruitment process is dependent on its advertisement, the impact of social media over this is tremendous. Social media and advertisements in electronic media have created newer and newer opportunity to share job details. Instead of this, rapid growth of opportunity to share job posts has increased the percentage of fraud job postings which causes harassment to the job seekers. So, people lacks in showing interest to new job postings due to preserve security and consistency of their personal, academic and professional information.Thus the true motive of valid job postings through social and electronic media faces an extremely hard challenge to attain people’s belief and reliability. Technologies arearound us to make our life easy and developed but not to create unsecured environment for professional life. If jobs posts can be filtered properly Predicting false job posts, this will be a great advancement for recruiting new employees. .Fake job posts create inconsistency for the job seekerto find their preferable jobs causing a huge waste of their time. An automated system to predict false job post opens a new window to face difficulties in the field of Human Resource Management.

2. LITERATURE SURVEY

Many researches occurred to predict if a job post is real or fake. A good number of research work sare to check online fraud job advertiser. Vidros [1] et al. identified job scammers as fake online job advertiser. They found statistics about many real and renowned companies and enterprises who produced fake job advertisements or vacancy posts with ill-motive. They experimented on EMSCAD dataset using several classification algorithms like naive bayes classifier, random forest classifier, Zero R, One R etc. Random Forest Classifier showed the best performance on the data set with 89.5% classification accuracy.

They found logistic regression performing very poor on the dataset. One R classifier performed well when they balanced the dataset and experimented on that. They tried in their work to find out the problems in ORF model (Online Recruitment Fraud) and to solve those problems using various dominant classifiers. Alghamdi [2] et al. proposed a model to detect fraud exposure in an online recruitment system. They experimented on EMSCAD dataset using machine learning algorithm.

They worked on this dataset in three steps- data pre-processing, feature selection and fraud detection using classifier. In the preprocessing step, they removed noise and html tags from the data so that the general text pattern remained preserved. They applied feature selection technique to reduce the number of attributes effectively and efficiently. Support Vector Machine was used for feature selection and ensemble classifier using random forest was used to detect fake job posts from the test data. Random forest classifier seemed a tree structured classifier which worked asensemble classifier with the help of majority voting technique. This classifier showed 97.4% classification accuracy to detect fake job posts.

Huynh [3] etal. proposed to use different deep neural network models like Text CNN, Bi-GRU-LSTM CNN and BiGRU CNN which are pre-trained with text dataset. They worked on classifying IT job dataset. They trained IT job dataset on Text CNN model consisting of convolution layer, pooling layer and fully connected layer. This model trained data through convolution and pooling layers. Then the trained weights were flattened and passed to the fully connected layer. This model used soft max function for classification technique. They also used ensemble classifier(Bi-GRUCNN, Bi-GRULSTMCNN) using majority voting technique to increase classification accuracy. They found 66% classification accuracy using Text CNN and 70% accuracy for Bi-GRU- LSTM CNN individually. This classification task performed best with ensemble classifier having an accuracy of72.4%.

Zhang [4]etal. proposed an automatic fake detect or model to distinguish between true and fake news (including articles, creators, subjects) using text processing. They had used acustom dataset of news or articles posted by Politick website twitter account. This dataset was used to train the proposed GDU diffusive unit model. Receiving input from multiple sources simultaneously, this trained model performed well a sanautomatic fake detector model.

Researchers experimented a good number of classifiers and feature selection technique to achieve good performance in the field of fake job post classification. Text processing using deep learning model, feature selection using support vector machine, data pre-processing etc. were mentioned approach to apply [8], [9], [10], [11], [12]. We have proposed to use deep neural network to predict job scams. We have applied the training method only on the categorical attribute of the EMSCAD dataset instead of using text data. This approach reduces the number of trainable attribute effectively with less processing time. We have made a comparative study on the same features of EMSCAD dataset using K Nearest Neighbor, Naive Bayes classifier, fuzzy KNN, decision tree, support vector machine,random forest classifier and neural network

3. PROPOSED SYSTEM

The system has used EMSCAD to detect fake job post. This dataset contains 18000 samples and each row of the data has 18 attributes including the class label. The attributes are job_id, title, location, department, salary range, company profile, description requirements, benefits, telecommunication, has company_ logo, has questions, employment type, required experience, required education, industry, function, fraudulent (class label). Among these 18attribute, we have used only7 attributes which are converted into categorical attribute.

The telecommuting, has_ company_ logo, has questions, employment type, required experience, required education and fraudulent are changed into categorical value from text value. For example, “employment type”values are replaced like this- 0 for “none”, 1 for ‘full-time”, 2 for “part-time” and 3 for “others”,4 for “contract’ and 5 for “temporary”. The main goal to convert these attributes into categorical form is to classify fraudulent job advertisements without doing any text processing and natural language processing. In this work, we have used only those categorical attributes

4. ADVANTAGES OF PROPOSED SYSTEM

The proposed has been implemented EMSCAD technique which is very accurate and fast. The system is very effective due to accurate detection of Fake job posts which creates inconsistency for the jobseeker to find their preferable jobs causing huge waste of their time.

5. LOGISTIC REGRESSION

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name logistic regression is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name multinomial Logistic regression is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likely hood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying grows that are not used during the analysis.

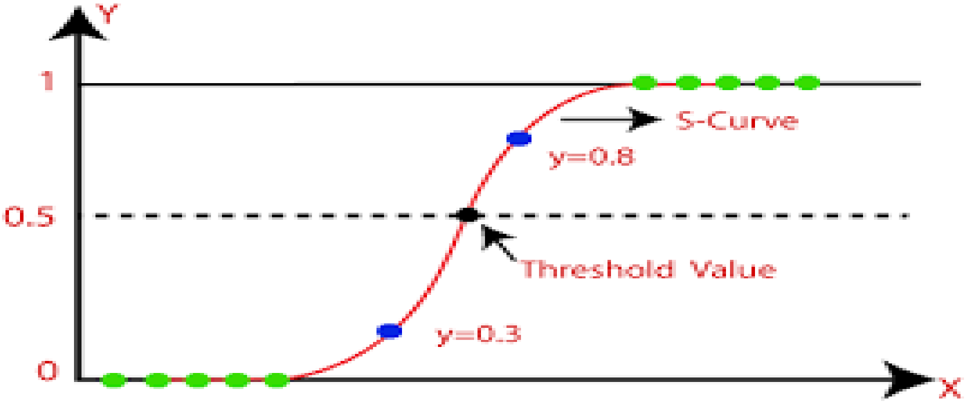


FIG 1: Logistic regression

6. NAÏVE BAYES CLASSIFIER

The naive bayes approach is a supervised learning method which is based on a simplistic chypothesis: it assumes that the presence (or absence)of a particular feature of a class is unrelated to the presence(or absence)of any other feature.

Yet, despite this, it appears robust and efficient. Its performance is comparable toother supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM(support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).

Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminate analysis and the linear SVM. We note that the results are highly consistent.

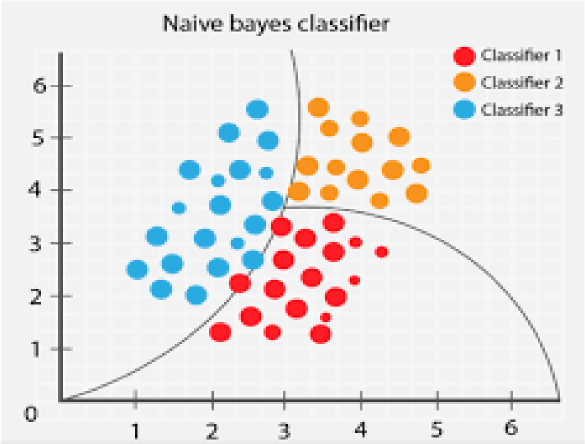


FIG 2: Naïvebayes

7. RANDOM FOREST CLASSIFIER

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of over fitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristic scan affect their performance. The first algorithm for random decision forests was created in 1995 by Tin KamHo[1] using the random sub space method, which ,in Ho's formulation ,is a way to implement the" stochastic discrimination" approach to classification proposed by Eugene Kleinberg. An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced firstby Ho [1] and later independently by Amit and Geman [13] in order to construct a collection of decision trees with controlled variance.

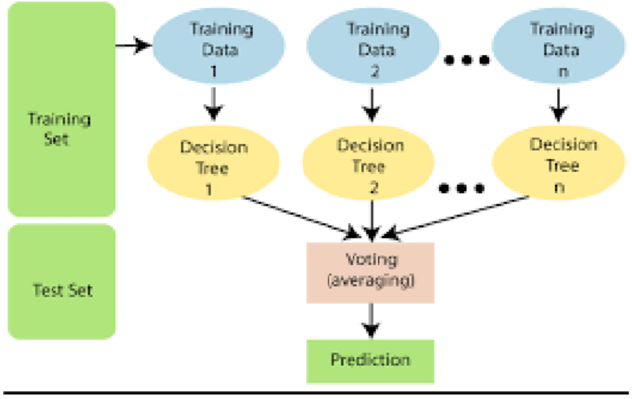


FIG 3: Random forest

8. SUPPORT VECTOR MACHINE

In classification tasks a discriminant machine learning technique aims at finding, based on an independent and identically distributed training dataset ,a discriminate function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data points and assigns it to one of the different classes that area part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space. The SVM kernel is a function that takes low-dimensional input space and transforms it into higher-dimensional space, i.e. it converts no separable problems to separable problems. It is mostly useful in non-linear separation problems. Simply put the kernel, does some extremely complex data transformations and then finds out the process to separate the database don the labels or outputs defined.

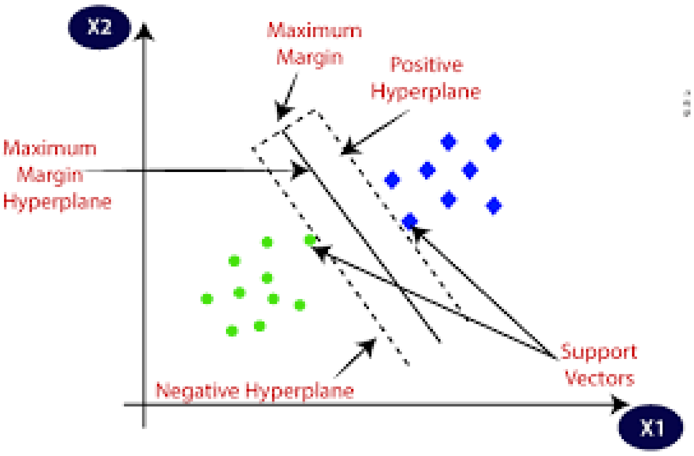


FIG 4 : SVM

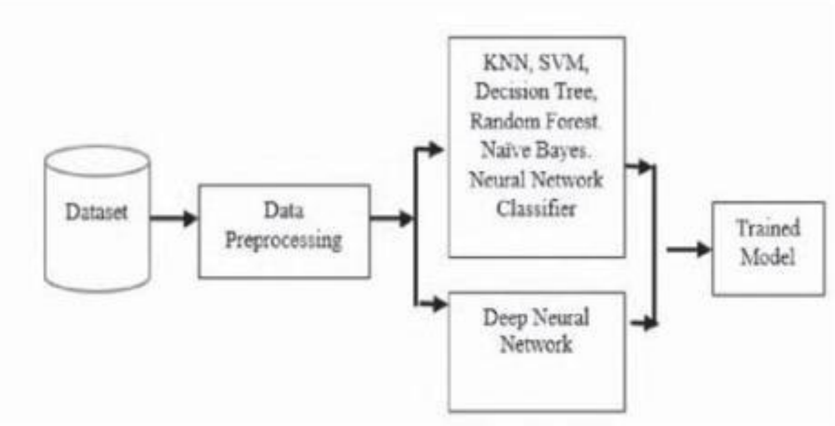
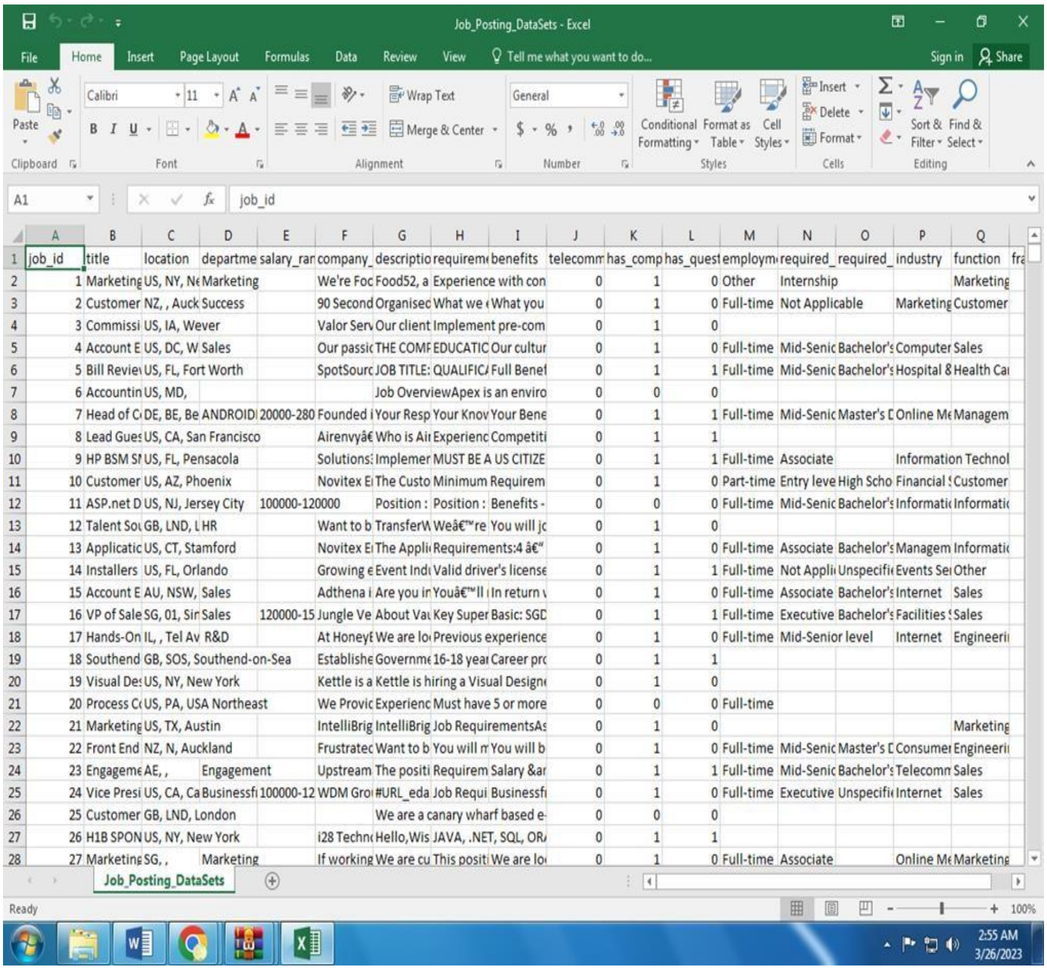

Dataset
Data Preprocessing
KNN, SVM, Decision Tree, Random Forest, Naive Bayes, Neural Network Classifier
Deep Neural Network
Trained Model

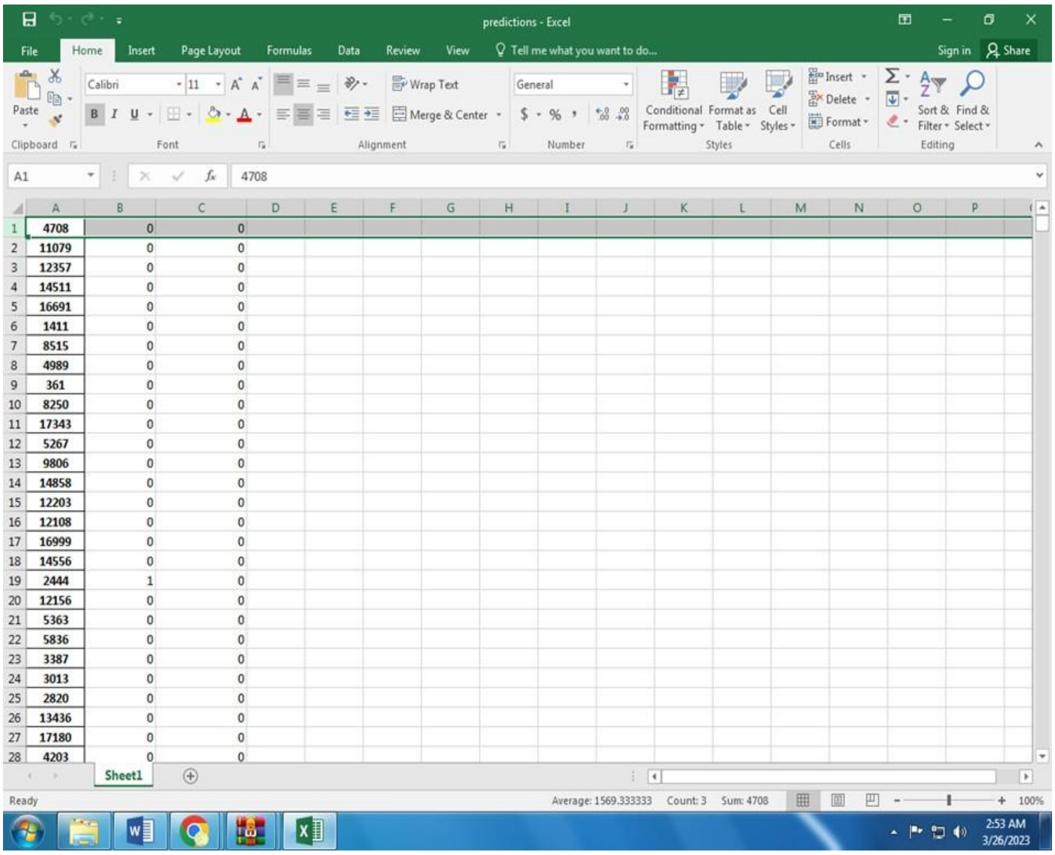
Fig. 1. Proposed Methodology

9. SAMPLE DATA SET OF JOB PREDICTION



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	job_id	title	location	departme	salary_ran	company_	descriptio	requireme	benefits	telecomm	has_comp	has_quest	employm	required_	required_	industry	function	fra
2	1	Marketing	US, NY, Ne	Marketing		We're Foc	Food52, a	Experience with con		0	1	0	Other	Internship			Marketing	
3	2	Customer	NZ, , Auck	Success		90 Second	Organised	What we (	What you	0	1	0	Full-time	Not Applicable		Marketing	Customer	
4	3	Commissi	US, IA, Wever			Valor Serv	Our client	Implement	pre-com	0	1	0						
5	4	Account E	US, DC, W	Sales		Our passic	THE COMF	EDUCATIC	Our cultur	0	1	0	Full-time	Mid-Senic	Bachelor's	Computer	Sales	
6	5	Bill Reviev	US, FL, Fort Worth			SpotSourc	JOB TITLE:	QUALIFIC/	Full Benef	0	1	1	Full-time	Mid-Senic	Bachelor's	Hospital &	Health Ca	
7	6	Accountin	US, MD,				Job OverviewApex is an enviro			0	0	0						
8	7	Head of C	DE, BE, Be	ANDROIDI	20000-280	Founded i	Your Resp	Your Knov	Your Bene	0	1	1	Full-time	Mid-Senic	Master's D	Online Me	Managem	
9	8	Lead Gues	US, CA, San Francisco			Airenvyâ€	Who is Air	Experienc	Competiti	0	1	1						
10	9	HP BSM SI	US, FL, Pensacola			Solutions:	Implemer	MUST BE A US CITIZE		0	1	1	Full-time	Associate		Information Technol		
11	10	Customer	US, AZ, Phoenix			Novitex E	The Custo	Minimum	Requirem	0	1	0	Part-time	Entry leve	High Scho	Financial S	Customer	
12	11	ASP.net D	US, NJ, Jersey City		100000-120000		Position :	Position :	Benefits -	0	0	0	Full-time	Mid-Senic	Bachelor's	Informatic	Informatic	
13	12	Talent Sou	GB, LND, L	HR		Want to b	TransferW	Weâ€™re	You will jc	0	1	0						
14	13	Applicatic	US, CT, Stamford			Novitex E	The Appli	Requirements:4 â€"		0	1	0	Full-time	Associate	Bachelor's	Managem	Informatic	
15	14	Installers	US, FL, Orlando			Growing e	Event Indu	Valid driver's license		0	1	1	Full-time	Not Appli	Unspecifie	Events Se	Other	
16	15	Account E	AU, NSW,	Sales		Adthena i	Are you in	Youâ€™ll (	In return v	0	1	0	Full-time	Associate	Bachelor's	Internet	Sales	
17	16	VP of Sale	SG, 01, Sir	Sales	120000-15	Jungle Ve	About Vau	Key Super	Basic: SGD	0	1	1	Full-time	Executive	Bachelor's	Facilities S	Sales	
18	17	Hands-On	IL, , Tel Av	R&D		At HoneyE	We are lo	Previous experience		0	1	0	Full-time	Mid-Senior level		Internet	Engineerii	
19	18	Southend	GB, SOS, Southend-on-Sea			Establishe	Governme	16-18 year	Career prc	0	1	1						
20	19	Visual Des	US, NY, New York			Kettle is a	Kettle is hiring a Visual Designe			0	1	0						
21	20	Process C	US, PA, USA Northeast			We Provic	Experienc	Must have 5 or more		0	0	0	Full-time					
22	21	Marketing	US, TX, Austin			IntelliBrig	IntelliBrig	Job RequirementsAs		0	1	0					Marketing	
23	22	Front End	NZ, N, Auckland			Frustratec	Want to b	You will m	You will b	0	1	0	Full-time	Mid-Senic	Master's D	Consumer	Engineerii	
24	23	Engageme	AE, ,	Engagement		Upstream	The positi	Requirem	Salary &ar	0	1	1	Full-time	Mid-Senic	Bachelor's	Telecomm	Sales	
25	24	Vice Presi	US, CA, Ca	Businessfi	100000-12	WDM Gro	#URL_eda	Job Requi	Businessfi	0	1	0	Full-time	Executive	Unspecifie	Internet	Sales	
26	25	Customer	GB, LND, London				We are a canary wharf based e-			0	0	0						
27	26	H1B SPON	US, NY, New York			i28 Techn	Hello,Wis	JAVA, .NET, SQL, OR/		0	1	1						
28	27	Marketing	SG, ,	Marketing		If working	We are cu	This positi	We are lo	0	1	0	Full-time	Associate		Online Me	Marketing	

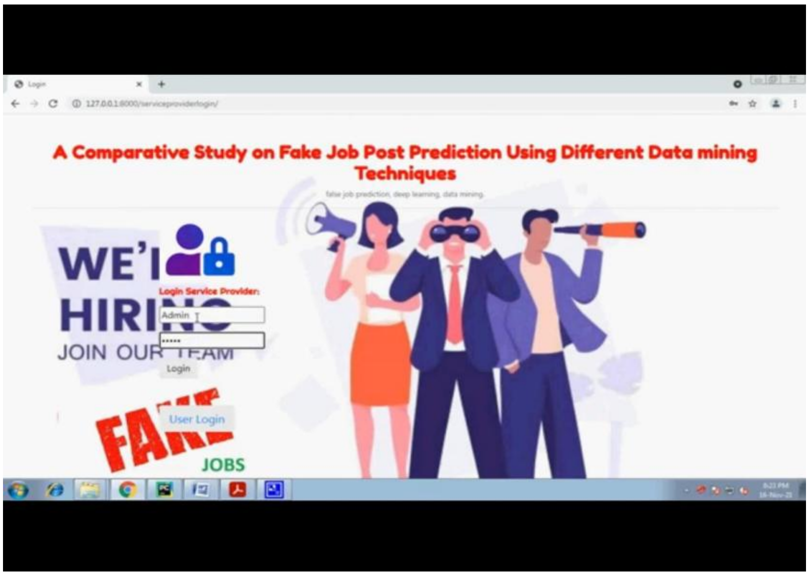
FIG 5 : DATASET



	A	B	C
1	4708	0	0
2	11079	0	0
3	12357	0	0
4	14511	0	0
5	16691	0	0
6	1411	0	0
7	8515	0	0
8	4989	0	0
9	361	0	0
10	8250	0	0
11	17343	0	0
12	5267	0	0
13	9806	0	0
14	14858	0	0
15	12203	0	0
16	12108	0	0
17	16999	0	0
18	14556	0	0
19	2444	1	0
20	12156	0	0
21	5363	0	0
22	5836	0	0
23	3387	0	0
24	3013	0	0
25	2820	0	0
26	13436	0	0
27	17180	0	0
28	4203	0	0

FIG 6 : DATASET

10. RESULTS



127.0.0.1:8000/serviceproviderlogin/

A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques

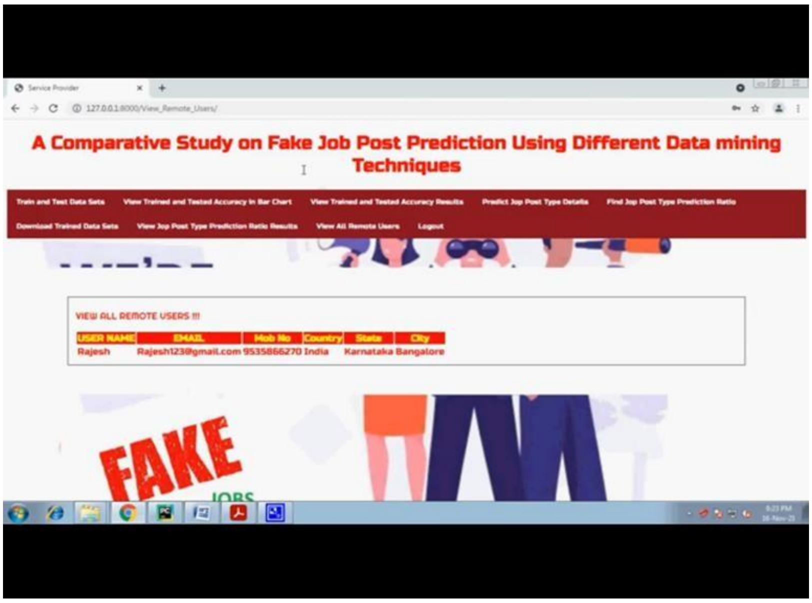
false job prediction, deep learning, data mining.

Login Service Provider:

Admin

•••••

FIG 7 : SIGN UP PAGE



127.0.0.1:8000/View_Remote_Users/

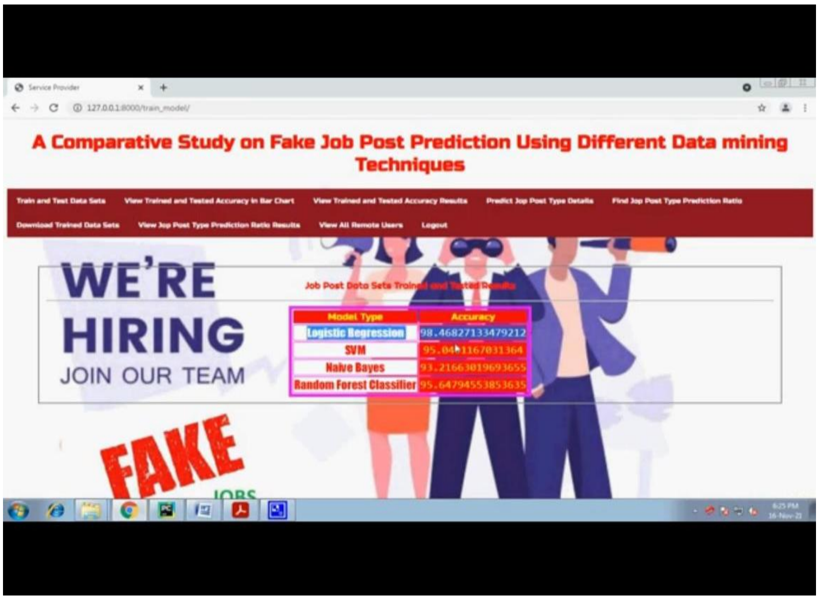
A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques

Service Provider
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
FAKE
JOBS

VIEW ALL REMOTE USERS !!!

USER NAME	EMAIL	Mob No	Country	State	City
Rajesh	Rajesh123@gmail.com	9535866270	India	Karnataka	Bangalore

FIG 8: VIEW ALL REMOTE USERS



127.0.0.1:8000/train_model/

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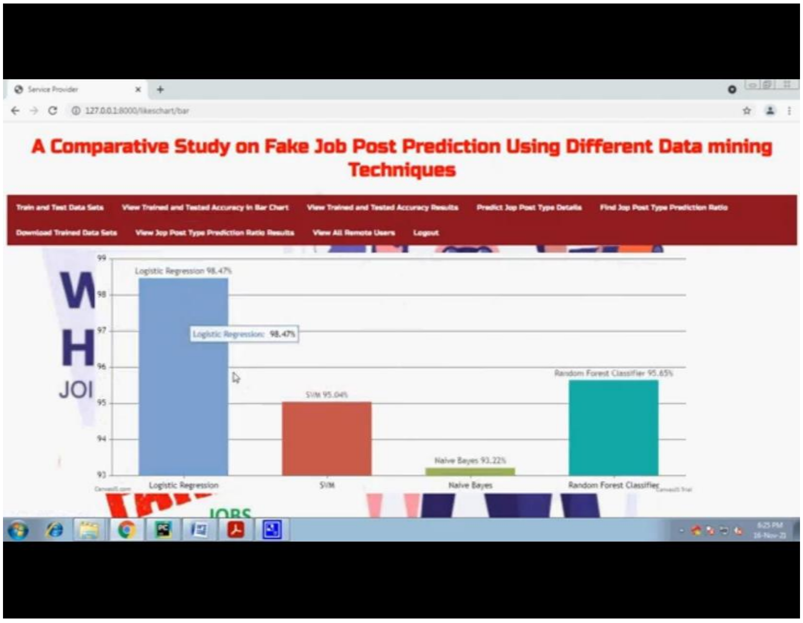
Service Provider
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
WE'RE
HIRING
JOIN OUR TEAM
FAKE
JOBS

Job Post Data Sets Trained and Tested Results

Model Type	Accuracy
Logistic Regression	98.46827133479212
SVM	95.04[illegible]1167031364
Naive Bayes	93.21663019693655
Random Forest Classifier	95.64794553853635

FIG 9 : AND TEST DATASETS



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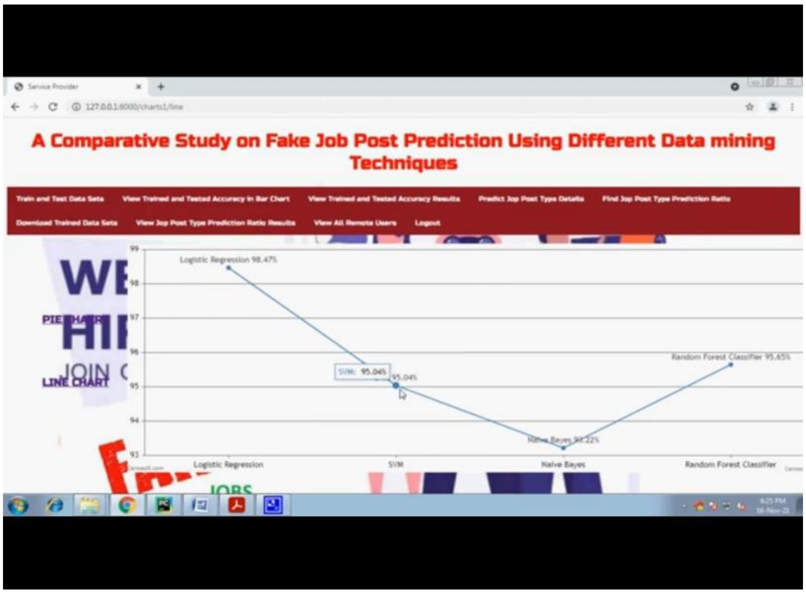
Service Provider
127.0.0.1:8000/likeschart/bar
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
99
98
97
96
95
94
93
Logistic Regression 98.47%
Logistic Regression: 98.47%
SVM 95.04%
Naive Bayes 93.22%
Random Forest Classifier 95.65%
Logistic Regression
SVM
Naive Bayes
Random Forest Classifier

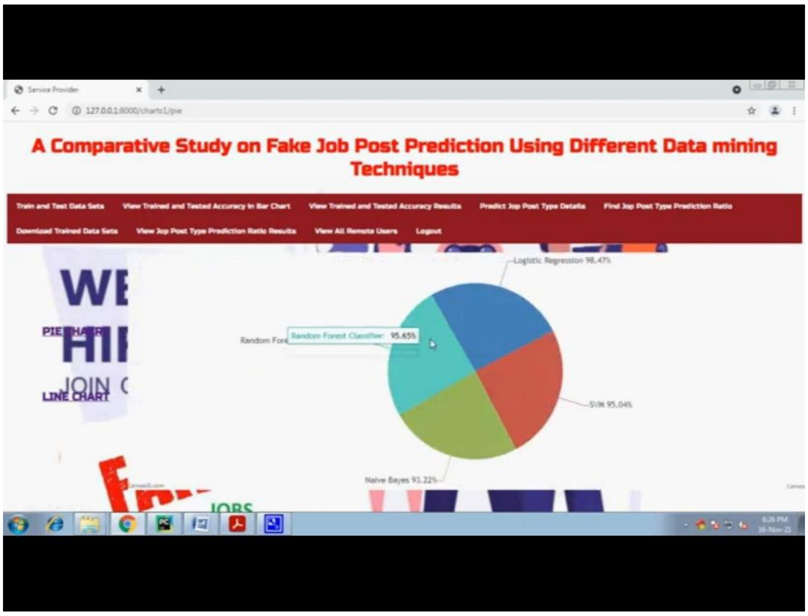
FIG 10: BAR GRAPHS



A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques

Service Provider
127.0.0.1:8000/charts1/line
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
99
98
97
96
95
94
93
Logistic Regression 98.47%
SVM: 95.04%
95.04%
Naive Bayes 93.22%
Random Forest Classifier 95.65%
Logistic Regression
SVM
Naive Bayes
Random Forest Classifier
PIE CHART
LINE CHART

FIG 11 ACCURACY GRAPHS



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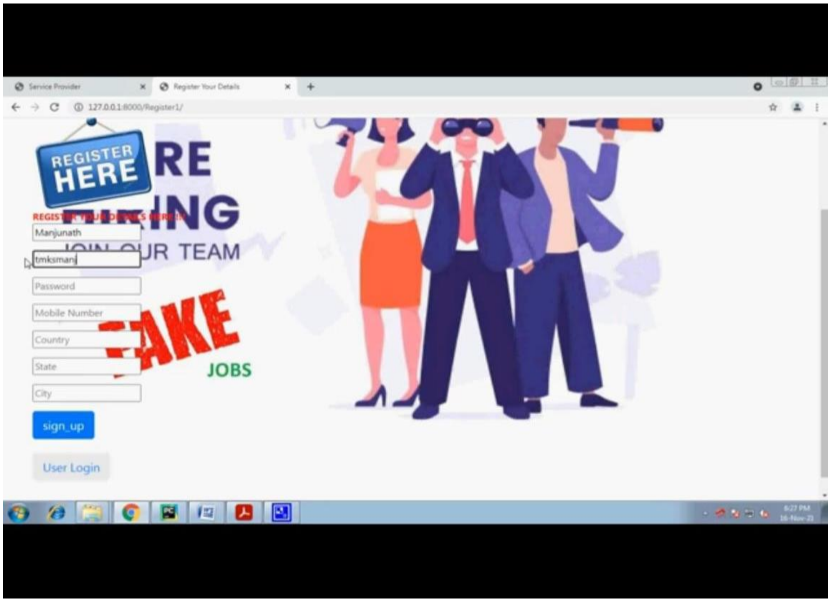
Service Provider
127.0.0.1:8000/charts1/pie
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
Logistic Regression 98.47%
Random Forest Classifier: 95.65%
SVM 95.04%
Naive Bayes 93.22%
PIE CHART
LINE CHART

FIG 12: PIE CHARTS



Manjunath

tmksmanj

FIG 13 : REGISTER

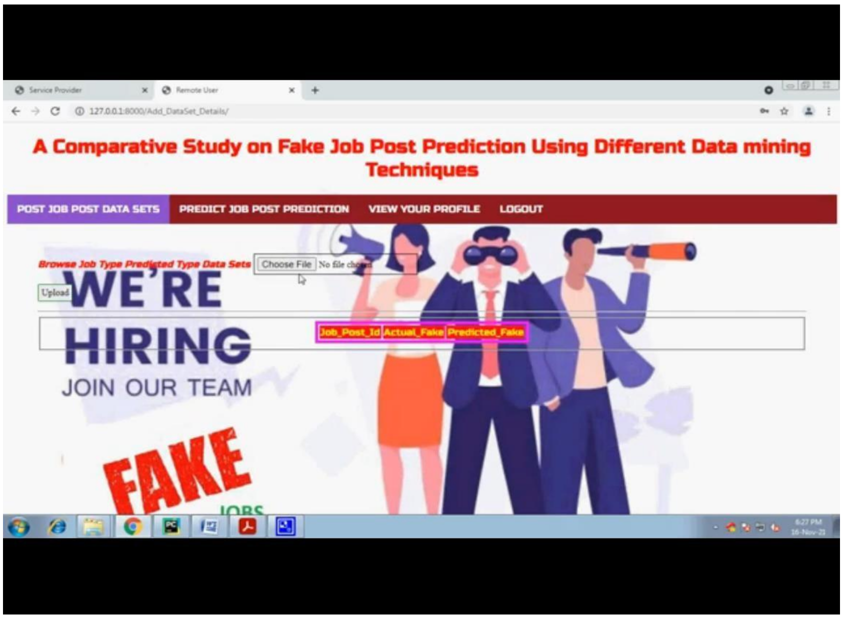
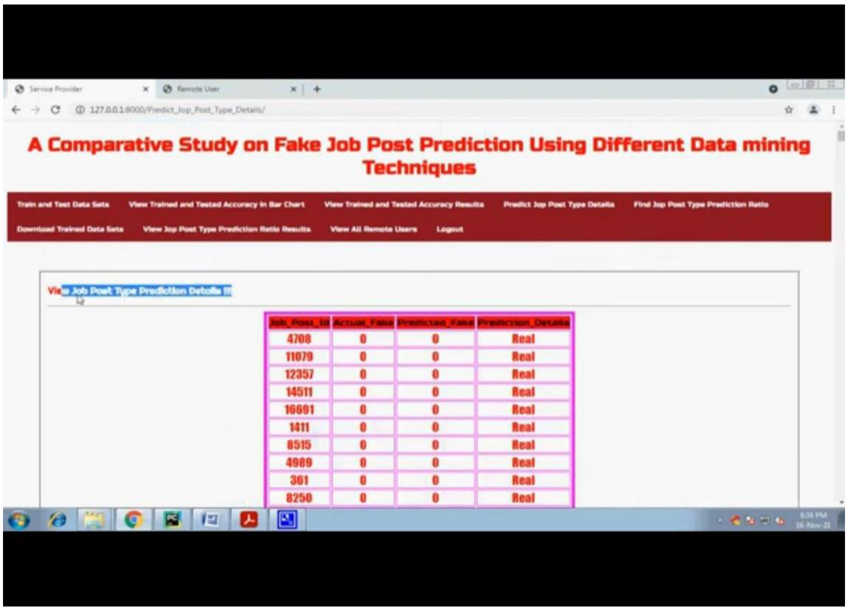

Service Provider
Remote User
127.0.0.1:8000/Add_DataSet_Details/
A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques
POST JOB POST DATA SETS
PREDICT JOB POST PREDICTION
VIEW YOUR PROFILE
LOGOUT
Browse Job Type Predicted Type Data Sets
Choose File
No file chosen
Upload
Job_Post_Id
Actual_Fake
Predicted_Fake
WE'RE HIRING
JOIN OUR TEAM
FAKE JOBS

FIG 14: POST JOB DATASETS

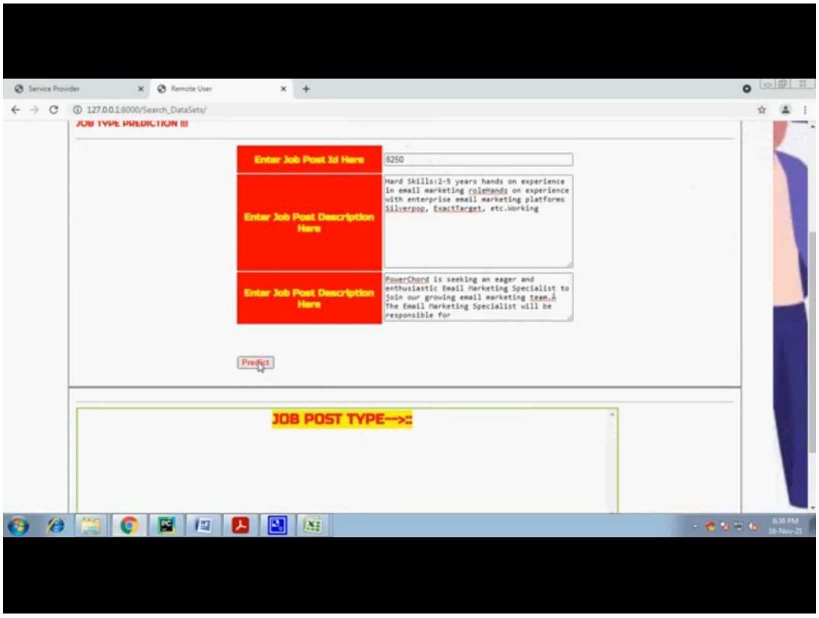

Service Provider
Remote User
127.0.0.1:8000/Predict_Jop_Post_Type_Details/
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout

A Comparative Study on Fake Job Post Prediction Using Different Data mining Techniques

View Job Post Type Prediction Details !!!

Job_Post_Id	Actual_Fake	Predicted_Fake	Prediction_Details
4708	0	0	Real
11079	0	0	Real
12357	0	0	Real
14511	0	0	Real
16691	0	0	Real
1411	0	0	Real
8515	0	0	Real
4989	0	0	Real
361	0	0	Real
8250	0	0	Real

FIG 15: FAKE AND REAL JOBS

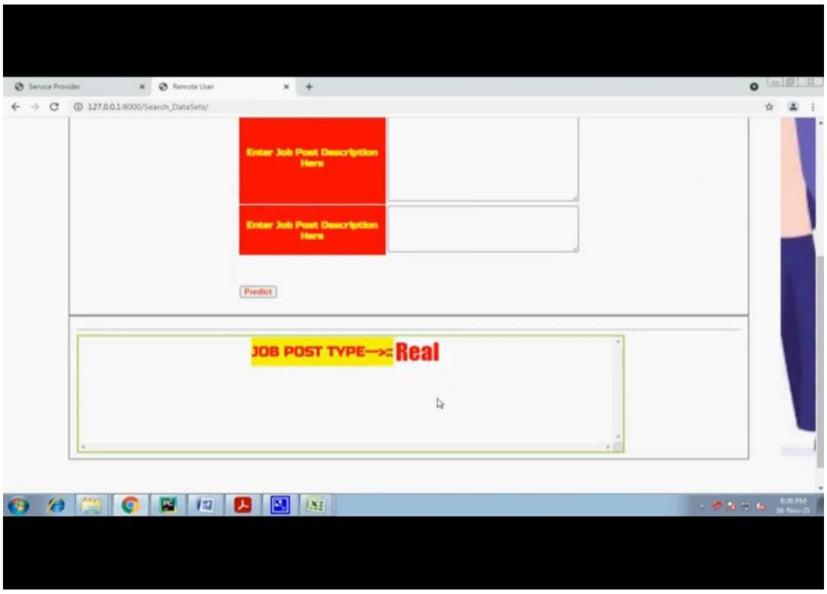


JOB TYPE PREDICTION !!!

Enter Job Post Id Here	8250
Enter Job Post Description Here	Hard Skills:2-5 years hands on experience in email marketing roleHands on experience with enterprise email marketing platforms Silverpop, ExactTarget, etc.Working
Enter Job Post Description Here	PowerChord is seeking an eager and enthusiastic Email Marketing Specialist to join our growing email marketing team.Â The Email Marketing Specialist will be responsible for

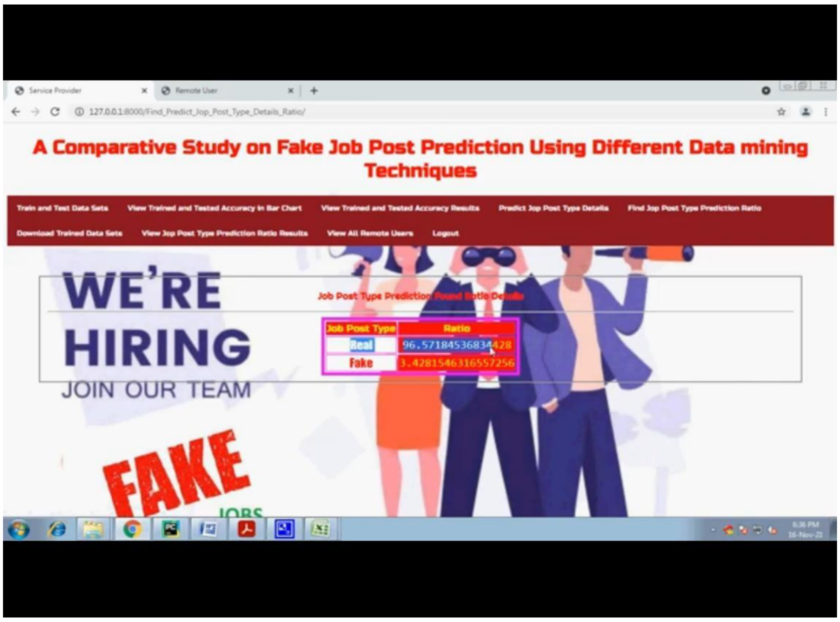
JOB POST TYPE-->:

FIG 16 : PREDICT FAKE AND REAL JOBS


Service Provider
Remote User
127.0.0.1:8000/Search_DataSets/
Enter Job Post Description Here
Enter Job Post Description Here
Predict

JOB POST TYPE-->: Real

FIG 17: PREDICTION STATUS


Service Provider
Remote User
127.0.0.1:8000/Find_Predict_Jop_Post_Type_Details_Ratio/
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
WE'RE HIRING
JOIN OUR TEAM
FAKE
JOBS

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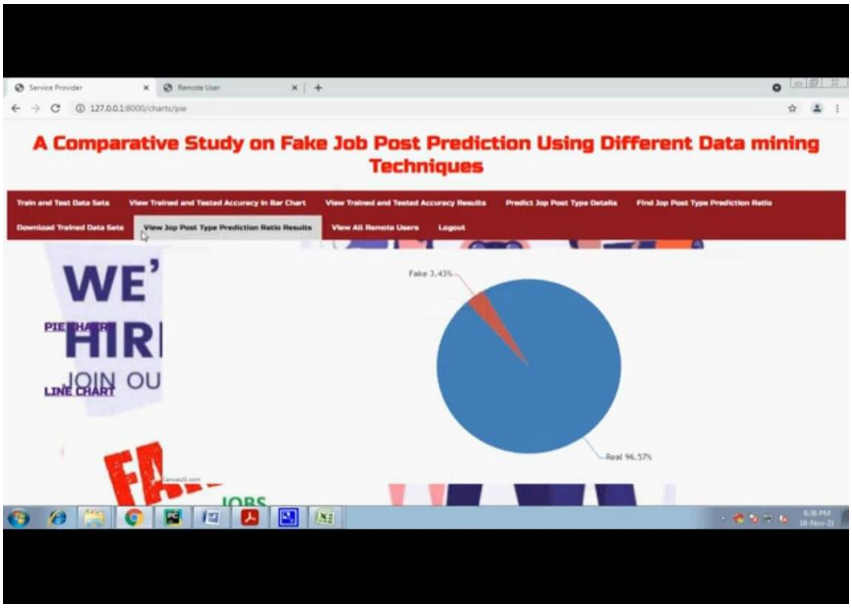
Job Post Type Prediction Found Ratio Details

Job Post Type	Ratio
Real	96.571845368344428
Fake	3.4281546316557256

FIG 18 : JOBPREDICTIONRATIO



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Service Provider
Remote User
127.0.0.1:8000/charts/pie
Train and Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
Predict Jop Post Type Details
Find Jop Post Type Prediction Ratio
Download Trained Data Sets
View Jop Post Type Prediction Ratio Results
View All Remote Users
Logout
PIE CHART
LINE CHART
Fake 3.43%
Real 96.57%

FIG 19: PIE CHART DISPLAYING RATIO

11. CONCLUSION

Job scam detection has become a great concern all over the world at present. In this paper, we have analyzed the impacts of job scam which can be a very prosperous area in research filed creating a lot of challenges to detect fraudulent job posts. We have experimented with Kaggle dataset which contains real life fake job posts. In this paper we have experimented both machine learning algorithms (SVM, Logistic Regression, Naïve Bayes, and Random Forest Algorithm).This work shows a comparative study on the evaluation of traditional machine learning. We have found highest classification accuracy for Random Forest Classifier among traditional machine learning algorithms and 99% accuracy for Logistic Regression.

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