Project Report Titled

TEXT CATEGORIZATION USING TF-IDF VALUE FOR A TEXTUAL DATASET AND PREDICTING THE CLASS LABEL FOR THE DOCUMENTS

Submitted in partial fulfillment of the requirements of the degree of Bachelor of Technology (Information Technology)

By

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DECLARATION OF STUDENTS

We declare that work embodied in stage-I of this Project titled "<u>Text Categorization Using</u> <u>Machine Learning Algorithm</u>" form our own contribution of work under the guidance of **Prof. Mahesh Shirole** at the Department of Computer Engineering and Information Technology, Veermata Jijabai Technological Institute. The report reflects the work done during period of Stage-I.

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Approval Sheet

CERTIFICATE

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students of B.Tech. (Information Technology), Veermata Jijabai Technological Institute, Mumbai have successfully completed the stage-I of project titled "<u>Text Categorization</u> <u>Using Machine Learning Algorithm</u>" under the guidance of **Prof. Mahesh Shirole**.

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ABSTRACT:

Considering the idea of predicting and classify of documents based on various features like the document text data and other metadata associated with the documents, along with generating labels for the list of documents. So we are going to classify the documents accordingly and generate a specified class for the dataset. For that we need to explore the fields of Machine Learning and provide an appropriate data classification model for the project. Most of the dataset is text based so many algorithms would be the perfect algorithm to predict and classify the documents according to the expected and obtained output.

INTRODUCTION:

Since the age of internet many of the sports, businesses, advertisement companies, political matters, etc documents are released in different languages and it's quite difficult to predict their documents type or category in which they fall and thus they land up at an unstable position for their expanding their agendas about the information they are providing. Thus our project comes into picture. The project mainly deals with the prediction and classification of the documents based on the text document they had provided along with the dataset. It is more convenient, reliable and also provides the user with wide range of classified and categorized data about the documents.

At first, we have to train our model to classify text data according to their label and provide the test dataset to the model. Thus error in the classification can be calculated. This allows our scope to improve the model.

We are about to use machine learning algorithm that provides appropriate string data classification with maximum accuracy.

MOTIVATION:

We can see the increase in the amount of information available online over various platforms available to us. Also we can see that the number of languages used for text categorization is present in abundance. With abundance of information in various languages, complexity in classification arises. As the text can be in English, Spanish, Italian or any regional languages like Marathi, Hindi. Thus we can't assign a class just comparing it to another language.

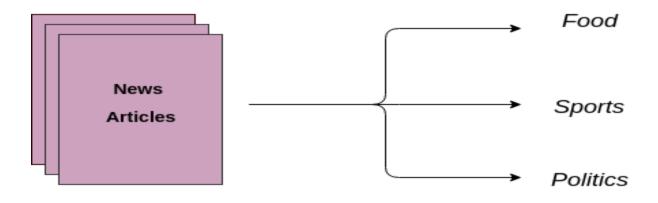
Text classification is different from binary classification. Multiple types of documents are present that is assigning a label to a document is not binary but requires much more computation. Not to cause any bias in assigning labels due to multiple classes is the main motivation behind the project.

PROBLEM STATEMENT:

Starting from the internet age, many more documents have been flooding over the internet. Lots and lots of documents are found within a minute. Thus assigning a binary class to a document is not preferred and it is not so convenient to do so. Also it is very important to classify these online documents for easy and fast access for computational purposes or finding anything on WWW. Our proposed system does the job of classifying and labeling a document its accurate class. Along with English text classification, we are also going to consider the Marathi text classification and label the documents perfectly. Two separate databases will be required for the algorithm to understand and classify the document accordingly.

LITERATURE SUMMARY:

Sentiment analysis is one of the most common use cases for classifiers. This kind of analysis is used detect positive or negative sentiment from a user or customer in their comments, tweets, reviews, etc. In language detection, an incoming piece of text will be analysed against a list of languages (e.g.: Spanish, English, French, etc.) to programmatically detect the language of the given text. Working with a set of apparel products and you want to automatically classify them using their descriptions. Text classification is often used for organize text by topic. This is commonly used for emails, support tickets, reviews, articles, etc. We can train a topic classifier to tag what incoming texts are about, provided that we provide associations between texts and tags that a machine learning model can learn from.



A number of extra text based features can also be created which sometimes are helpful for improving text classification models. Some examples are:

Textual Feature:

- Text Length The count of characters in the documents text, including punctuation and spaces.
- Character Count The number of alphabetical characters in the documents text.
- Word Count The number of words in the documents.
- Unique Word Count The number of unique words in the documents.
- Sentence Count The number of sentences in the documents.
- Automated Readability Index, the automated readability index score, which is a measure of text readability, can be computed.
- Frequency distribution of Part of Speech Tags:
 - Noun Count
 - Verb Count
 - Adjective Count
 - Adverb Count
 - o Pronoun Count

LITERATURE SUMMARY REVIEW:

These topics discuss the work done by the various authors, students and researchers in brief under the domain of classification and pre-processing the textual data.

SR .no	Title of paper, publisher /event	Autor of public ation	Proble m they solved	Technolo gy they used	Metho dology used	Input provid ed	Output obtained	Summary of work	Future work proposed/ possible extension of work
1	Text Categoriz ation with Support Vector Machines : Learning with Many Relevant Features	Thorst en Joachi ms	Classifi cation of Text Docum ent	Polynom ial and RBF kernels	SVM	Text Docu ment	Text classificati on based on predefined categories	It uses Support Vector Machine for the text classification. They are fully Automated and eliminate the need of manual parameter turing. The document may fall in multiple, one or not any of the categories. The representation of each category is treated as separate binary classification. With the information retrival system, the documents are transformed into representable format for the learning algo and classification task. Ordering of the words doesn't matter so it generates the category for the corresponding word in the set including its number of repetition. It has a very high dimensional feature sets which doesn't over-fit the feature set for classification and also generalizes the accuracy.	SVMs do not require any parameter tuning, since they can nd good parameter settings automaticall y. All this makes SVMs a very promising and easy-to-use method for learning text classifiers
2	Interactio n of	Janez Brank	Classifi cation	Tensorflo w	SVM, differ	Text Docu	Text classificati	The method SVM and other classifier for	Expand the study to

	Г .		Cm :		,		1 1	1	1.1%
	Feature	,	of Text		ent	ment	on based	better accuracy. The	additional
	Selection	Mark	Docum		classif		on	Naïve Bayes Classifier,	classifiers,
	Methods	0	ent		ier ie.		predefined	Perceptron-I, Linear	linear and
	and	Grobe			Naïve		categories	SVM is used as the	non-linear,
	Linear	lnik			Bayes			classifier. One of the	and
	Classifica				,			classifier's weaknesses	diversify
	tion				Perce			can be hindered by	the feature
	Models				ptron-			another. Using this	scoring
					I.			concept, the	algorithms
					Linear			classification is done.	to include
					SVM			Here the feature	those that
					D V IVI			selection is done in two	possibly
									include
								ways. One is using full	
								features set and second	information
								one is using selected	of feature
								features set and study	dependencie
								them for future	s or similar
								references for linear	characteristi
								classification. Feature	cs, leading
								selection is based on	to more
								score of the feature.	sophisticate
								Top ranked are kept	d data
								while other are	modeling.
								discarded.	
								It has seen the SVM has	
								outperformed	
								perceptron- based and	
								Naïve Bayes- based	
								classifiers for the text	
								categorization.	
3	An	Ana	Classifi	ModApt	Latent	Messa	Aggioning	The classification is	We plan to
)				1			Assigning		-
	Empirical		cation	e	Sema	ges	one or	based on the messages,	investigate
	Comparis	soCac	of Text		ntic	and	more	newsgroups and	if further
	on of	hopo	Docum		Analy	News	number of	categorized into 10	improveme
	Text	and	ent		sis	group	Text	different sections. Both	nts can be
	Categoriz	Arlind			(LSA)		Categoriza	the inputs are used for	applied to
	ation	0			,		tion	comparing the SVM	the SVMs
	Methods	Limed			SVM,			and LSA results. Pre-	and k-NN
		e			KNN			processing of dataset is	LSA
		Olivei						done by removing	models. If
		ra						words with length	possible,
								smaller than 3 or	this would
								greater than 20.	further
								Removed numbers,	enhance the
								made the upper and	superiority
								lower cases same. The	of these
								tf-idf (term frequency –	methods
								inverse document	observed in
									this
								frequency) is used for	
								computing the index	experiments

4	Integrating Feature and Instance Selection for Text Classification	Dimit ris Frago udis,D imitris Meret akis, Spiros Likot hanaS sis	Classifi cation of Text Docum ent	ModApt e- training- test, Newsgro up, Reuters	FIS (Feature and Instance Selection)	Text Docu ment	Text classificati on based on predefined categories	term weight of a document. The LSA then lowers the dimension of the original set of vectors with the new ones which comprises mostly a generalized word or class for the document. It is seen that k-NN LSA shows more promising classification than any other used method. Most of the time feature selection does the job of reducing the dataset. Thus the FIS algorithm pre-processes the dataset by selecting the features and instances then dataset is provided to algorithm. Naïve Bayes, TAN and LB classifier has produced better results with resultant dataset of FIS algorithm. Also provides best result compared to SVM. The results were compared between MI (Mutual Information) and FIS dataset classifier. It was observed that FIS had more promising results than MI. Naïve Bayes, TAN and LB algorithm used the data set which was the resultant dataset of the MI and FIS. Among which FIS	Can be extend FIS for dealing with multiclass problems and to apply it to structured data in addition to text.
	D :	T'1	C1 : "	NG:	773737	T	TD :	had more accurate results.	<u> </u>
5	Pruning Training Corpus to Speedup Text Classifica	Jihon g Guan, Shuig eng Zhou	Classifi cation of Text Docum ent	VC++ 6.0 under Windows 2000, PC with P4 1.4GHz	KNN	Text Docu ment	Text classificati on based on predefined categories	The method is based on the pruning of dataset by clustering method. The classification is done by using the KNN and Linear classifier.	Improves by the factor of larger than 4, with less than 3%

	1 -	1	_	1		П	T	I —.	
	tion			CPU and				They both alone are not	degradation
				256MHz				efficiently producing	of micro-
				memory				results as they can by	averaging
								doing both. Firstly the	performanc
								clustering calculates the	e. So can be
								difference between the	put to use
								documents vector as	where
								corresponding to	unnecessary
								features selected. By	features are
									bulk or
								treating each training class as a distinctive	irrelevant.
									meievant.
								cluster, then using a	
								genetic algorithm to	
								select a subset of	
								document features such	
								that the difference	
								among all clusters is	
								maximized. The	
								pruning method has	
								dataset of document D.	
								A document d also has	
								other documents in its	
								classified class. The	
								features and similarities	
								score of the document	
								is tallied with the Class	
								in Dataset D. Thus we	
								are pruning the dataset	
								For further	
								classification based on	
								the score of a document	
								and selecting only the	
								class which has the	
								score near to the	
								document.	
6	Acquecay	Xuexi	Classifi	ModAnt	Euclid	Text	Text	The procedure of the	Can be used
U	Accuracy		cation	ModApt		Docu	classificati	automatic text	where
	improve	an		e-	ean		on based		
	ment of	Han	of Text	training-	distan	ment		classification consists	biased
	automatic	Guow	Docum	test,	ce,		on	of four general steps for	dataset
	text	ei Zu,	ent	Newsgro	SVM-		predefined	feature vector	comes into
	classifica	Watar		up,	Linear		categories	generation, dimension	picture with
	tion	u		Reuters.	,			reduction, learning and	multiple
	based on	Ohya			Linear			classification. The	dimensional
	feature	mal			discri			study done in this report	ity.
	transform				minan			tells us that the use of	
	ation and				t			multiple classifiers can	
	Multi-				functi			be done for better and	
	classifier				on,			efficient classification	
	combinat							of documents. The	
	ion							classifiers alone are not	

7	Combining Multiple K- Nearest Neighbour Classifier s for Text Classifica tion by Reducts	Yongg uang Bao and Naohi ro Ishii	Classifi cation of Text Docum ent	ModApt e- training- test, Newsgro up, Reuters.	K- neares t Neigh bour, KNN Classi fier, RkNN	Text Docu ment	Text classificati on based on predefined categories	efficient enough but the working together it overcomes each- others drawback. Based on the score of the document's feature, dataset can be reduced dimensionally if the feature doesn't have the needed count. Among all the classifiers, the SVM-Linear had the best outcome with reduced dimensionality. It uses basic K- nearest neighbour for the classification. Alone K-nearest neighbour is sufficient so multiple feature set has been put to use. It combines multiple KNN classifiers. To select the feature of the subset, the MFS were build on trail and error. To overcome this problem, random selection of MFS was done. This made the problem NP-hard. The multiple reducts can be formulated precisely and in a unified way within the framework of Rough Sets theory. This theory generates multiple reducts which improves the performance of KNN classifier. In text classification,	Multiple reducts to improve the performanc e of the k- nearest neighbor classifier which is easiest classifier. So future use might be restricted.
o	Selection using Improved Mutual Informati on for Text Classifica	Novo vicov a, Anton on Malik and Pavel	cation of Text Docum ent	Reuters	Bayes Classi fier, Best indivi dual featur es(BI	Docu ment	classificati on based on predefined categories	usually a document representation using a bag-of-words approach is employed. This representation scheme leads to very high dimensional feature space. A predefined	of future work remain. Ongoing work includes comparison on the other

		D 1'1		1	T'	l	1	1 0.1 1	
	tion	Pudil			F),			number of the best	text
					Seque			features are taken to	classifiers,
					ntial			form the best feature	for
					forwa			subset. Scoring of	example,
					rd			individual words can be	support
					selecti			performed. Best	vector
					on			individual features	machines
					(SFS)			(BIF) methods evaluate	and k-
					, ,			all the n words	nearest
								individually according	neighbor.
								to a given criterion, sort	8
								them and select the best	
								k words. Sequential	
								forward selection (SFS)	
								methods firstly select	
								the best single word	
								evaluated by given	
								criterion. Then, add one	
								word at a time until the	
								number of selected	
								words reaches desired k	
								words. r SFS methods	
								do not result in the	
								optimal words subset	
								but they take note of	
								dependencies between	
								words as opposed to the	
								BIF methods. Therefore	
								SFS often give better	
								results than BIF.	
9	Discretizi	Pio	Classifi	Reuters	AdaB	Text	Text	Based on the idea of	AdaBoost.
	ng	Nardi	cation	and	oost	Docu	classificati	adaptive boosting, a	MH is in
	Continuo	ello,	of Text	newsgro		ment	on based	version of boosting in	the
	us	Fabriz	Docum	up			on	which members of the	restricted
	Attribute	io	ent	1			predefined	committee can be	lot of the
	s in	Sebast					categories	sequentially generated	peak text
	AdaBoos	iani,					Control	after learning from the	categorizati
	t for Text	and						classification mistakes	on
	Categoriz	Aless						of previously generated	performers
	ation	andro						members of the same	nowadays, a
	WI () II	Sperd						committee,	lot where
		uti						AdaBoost.MH is a	the margins
		uti						realization of the well-	for
								known AdaBoost	
									performanc
								algorithm, which is	e
								specifically aimed at	improveme
								multi-label TC4, and	nt are
								which uses decision	slimmer and
								trees composed of a	slimmer.
					<u> </u>			root and two leaves	

		1	ı	T	1	1	T		
								only as weak	
								hypotheses. Algorithms	
								attempt to optimally	
								split the interval on	
								which these attributes	
								range into a sequence of	
								disjoint subintervals.	
								This split engenders a	
								new vector (binary)	
								representation for	
								documents, in which a	
								binary term indicates	
								that the original non-	
								binary weight belongs	
								or does not belong to a	
								given sub-interval	
10	A	Yamin	Classifi	Doutons	KNN,	Text	Text		Eases the
10			cation	Reuters, OHSUM	Linear	Docu	classificati	Document Frequency (DF) Threshold is the	computation
	comparat	g Yang,	of Text	ED	Least		on based	simplest for vocabulary	and power
	ive study	Jan O	Docum			ment		reduction. Easily scales	over the
	on feature	Peder			Squar e Fit		on prodofined	_	
			ent				predefined	to very large corpus.	application used for
	selection	son			(LLS		categories	Due to widely received	
	in text				F),			assumption of info	high level
	categoriz				Docu			retrival, DF is not used.	performanc e. From
	ation				ment			The Information Gain	
					freque			(IG) measures the bit of	Neural
					ncy,			information and obtains	Network to
					Infor			the category of the	Text
					matio			document by the	categorizati
					n			presence or absence of	on The
					gain,			terms. With each term	methods
					Chi-			Information gain is	can be used
					test			calculated and few are	significantly
								discarded which has	•
								less value than already	
								predefined threshold.	
								Thus conditional	
								probability is put to use	
								for term t and category	
								c. The Chi-test	
								measures the lack of	
								independence between	
								the term t and category	
								c and can be compared	
								to Chi square	
								distribution with one	
								degree of freedom.	
								Thus the IG or DF	
								combined with KNN or	
								LLSF gives us efficient	

								results for the classification.	
11	"Text Categoriz ation with Support Vector Machines."	Machi ne Learni ng, 46, 423– 444, 2002 c ,2002 Kluwe r Acade mic Publis hers. Manuf acture d in The Nether lands	Classific ation of text docume nt	linear kernel, 2nd order polynomi al kernel, Gaussian rbf-kernel	SVM	Text docum ent	text classificatio n, lemmatizati on, stemming	In this we study about (SVM) support vector machines. The SVM are capable of effectively processing feature vectors of some 10 000 dimensions, given that these are sparse. And also support vector machines provide a fast and effective means for learning text classifier's from examples we study different mappings of frequencies to input space, and combine these mappings with different kernel functions	In future work we want to see if the results can be generalized to other languages i.e. Slavic, romance, and non-Indo- Europeans. If the results were positive, a generic algorithm would be found that worked well on nearly any language.
12	1. Text categoriza tion based on Concept indexing and principal componen t analysis.	Ke H., Shaop ing M 2002	They find that this algorith m can effective ly reduce dimensi onality without sacrifici ng categori zation accurac y.	salton	Conce pt indexi ng, princi ple comp onent analys is, Vsm,K NN,Ba ysean classifi er.	Text docum ent	Classified data on	They uses the vector space model and feature selection of the text document is represented by a vector and all subsequent calculation based, many ML technology have been successfully applied to text categorization. Concept indexing is simple and effective way to reduce dimension. For effective in data compression and feature extraction we use PCA,they applied pca to ci subspace.	This method for put forwarded in the paper is meaningfull to online text categorisatio n, application of more machine learning.
13	"Improvin g SVM Text Classificat ion Performan ce through Threshold Adjustme nt"	Clairv oyance Corpor ation, 5001 Baum Boule vard, Suite 700, Pittsbu	Classific ation of text docume nt	Corpora, threshold adjusting algorithm	SVM	Text docum ent	automatic process for adjusting the thresholds of generic SVM which incorporate s a user utility	In general, support vector machines (SVM), when applied to text classification provide excellent precision, but poor recall. So to improve Recall we customizing SVMs. Customizing Means to adjust the threshold	the proposed thresholding approach is independent of the learnt model, using it in conjunction with other types of models will

14	"Feature Selection	rgh, PA 15213- 1854, USA Pedro A. C.	Classific ation of	Tensorflo w	multi-	huge networ	model, an integral part of an information manageme nt system Improve Document	associated with an SVM. We describe an automatic process for adjusting the thresholds of generic SVM which incorporates a user utility model, an integral part of an information management system In this we use the feature selection algorithms were	also form an interesting aspect of future work.
	Algorithm s to Improve Document s Classificat ion Performan ce"	Sousa 1, João Paulo Piment ão1, Bruno René D. Santos 2, and Fernan do Moura -Pires3	text docume nt		system s, feature selecti on, Inform ation retriev al , text learnin g	k infrast ructure s and new inform ation, text docum ent		evaluated in order to improve documents' classification performance	documents' classification performance.
15	"An evaluation of statistical approache s to text categoriza tion."	Yimin g Yang yiming @cs.c mu.ed u April 10, 1997	Classific ation of text docume nt	Corpus, categoriza tion methods	KNN, LLSF ,neural networ k and WOR D, cross metho d evalua tion	Text docum ents, previo usly publis hed results and newly obtain ed results	Improve Text	This paper is a comparative study of text categorization methods. Fourteen methods are investigated, based on previously published results and newly obtained results from additional experiments. Corpus biases in commonly used document collections are examined using the performance of three classifiers. Problems in previously published experiments are analyzed, and the results of flawed experiments are excluded from the cross-method evaluation. As a result, eleven out of the fourteen methods are remained. A k-nearest neighbor (kNN) classifier was chosen for the performance baseline on several collections; on each collection, the performance scores of other methods were	for improving documents' classification performance.

			T	I	1			1 1 1 1	
								normalized using the score of kNN. This	
								provides a common basis	
								for a global observation	
								on methods whose results	
								are only available on	
								individual collections.	
								Windrow-Hoff, k-nearest	
								neighbour, neural	
								networks and the Linear	
								Least Squares Fit	
								mapping are the top-	
								performing classifiers,	
								while the Roccio	
								approaches had relatively	
								poor results compared to	
								the other learning	
								methods. KNN is the only	
								learning method that has	
								scaled to the full domain	
								of MEDLINE categories,	
								showing a graceful behaviour when the target	
								space grows from the	
								level of one hundred	
								categories to a level of	
								tens of thousands	
								An Evaluation of	
								Statistical Approaches to	
								Text	
16		Ke H.,	They	salton	Conce	Text	Classified	They uses the vector	This method
	Text	Shaop	find that		pt	docum	data on	space model and feature selection of the text	for put
	categoriza tion	ing M	this		indexi	ent		document is represented	forwarded in the paper is
	based on		algorith m can		ng,			by a vector and all	meaningfull
	Concept	2002	effective		princi			subsequent calculation	to online text
	indexing		ly		ple			based, many ML	categorisatio
	and		reduce		comp			technology have been	n, application
	principal		dimensi		onent			successfully applied to	of more
	componen		onality		analys			text categorization.	machine
	t analysis.		without		is,			Concept indexing is	learning.
			sacrifici		Vsm,K			simple and effective way	
			ng .		NN,Ba			to reduce dimension. For	
			categori		ysean			effective in data	
			zation		classifi er.			compression and feature	
			accurac		C1.			extraction we use PCA,they applied pca to	
			у.					ci subspace.	
17		Kehag	: (a) in	Wordnet	MAP,		Classified	They work with WordNet	Nevertheless,
-	A	ias A.,	compar	lexical	ML,v	Lexica	data	lexical database and	in a practical
	Comparis	Petrid	ing the		erson	1		distinction between the	classification
	on of	is V.,	merit of		space,	databa		word and senses. It	task the
	Word- and	Kabur	words		KNN,	se		contains the large number	senses would
	Sense-	lasos	and		Recur			of noun, verb etc of	have to be
								English language	obtained by a

1									
	based Text Categoriz ation Using Several Classificat ion Algorithm s.	V., Fragk ou P 2003	senses as classifi cation features and (b) in testing several classific ation algorith ms on the Brown Corpus		sive Versio n of the MAP algorit hm, Maxi mum Likeli hood (ML) Classi ficatio n			.WordNet provide carefully worked out word and sense vocabularies for English language, as well as the membership of each word into a number of senses.the document they have used in their text categorisation experiment use a subset of the brown corpus .for document representation they used 4 document representation two are word based and two are sense based. And classify algorithm uses are Maximum a posteriori (MAP) classification, batch version, recursive version of MAP algorithm, maximum Likelihood classification and FLNMAP with voting.	disambiguati on step which, in all probability, would introduce a significant error
17	Automatic detection of text genre.	B. Kessl er, G. Nunb erg, and H. Schut ze.	They propose a theory of genres as bundles of facets, which correlate with various surface cues, and argue that genre detectio n based on surface cues is as successful as	Computational linguists	Corpu s logisti c Regre ssion , Neura l Netw ork,	Text data	Classified data on basis of linguistics.	They first linguistic research on genre that uses quantitative method then identify the genres: genetic cues, these cues that have figured prominently in previously work on genre.then applied method like corpus, logistic Regression, Neural Network. For each genre facet, it compare our result using surface cues.	This theory used in application of genre classification to tagging, summarizatio n.

			detectio						
			n based						
			on						
			deeper						
			structura						
			l proporti						
			properti es.						
19		Karl-	In this	Search	Rule	Text	Classified	Here they used text	The main
	Technique	Micha	they	engine,	induct	docum	clustered	document data then then	contribution
	s for	el	demonst	web	ion,	ent	document	classifying these data by	of this paper
	Improving	Schne	rate that	kernel	Naïve			the help of naïve bays	is our novel
	the Performan	ider	simple modific		bays ,			classifier, in these Bayesian text	feature
	ce of		ation are		decisi			classification uses a	scoring function,
	Naive 01	2002	able to		on			parametric mixture model	which is able
	Bayes for		improve		tree,su			to model the generation of	to distinguish
	Text		the		pport			document.to make the	features that
	Classificat		perform		vectr			estimation of parameters	improve the
	ion		ance of		machi			tractable, we make the	clustering of
			Naïve		ne,			Naïve Bayes assumption	the training
			Bayes		cluste			that the basic units are	documents
			for text		ring			distributed independently.	(and thus are
			classific					For the highly	useful for classification
			ation significa					classification accuracy than binary independence) from
			ntly.					model on text document	features that
			nay.					because it model word	degrade the
								occurrence frequency one	clustering
								can see that for longer	quality (and
								document the	thus should
								classification scores	be removed)
								dominated by the word	
								probabilities and the	
								probabilities hardly affect the classification. Feature	
								selection is commonly	
								regarded as a nessarry	
								step in text classification.	
								By taking logarithms and	
								dividing by the length of a	
								document, instead of	
								multiplying conditional	
								probabilities they	
								calculate their geometric	
								mean and thus account for the impact of wrong	
								independence	
								assumptions under	
								varying document	
								lengths. Furthermore, by	
								adding the entropy of (the	
								probability distribution	
								induced by) the	
								document, we account for	

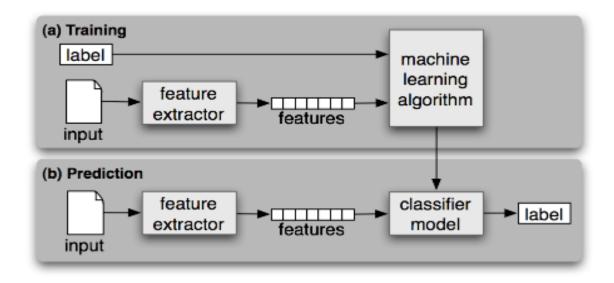
	1	1			1		<u> </u>		<u> </u>
								varying document	
6.0		771	Tr:	X Y	DE C	*	G1 10 1	complexities.	
20	**	Klopo	. The	Natural	ETC	Large	Classificati	In these work they used	empirical
	Very	tek M.	paper	language	algorit	data	on of input	ETC described in details,	evaluation of
	Large	and	presents	possessin	hm,	like	large data.	it constructs a tree-like	a Bayesian
	Bayesian	Woch	results of	g task.	naïve	search		Bayesian network but	multinet classifier
	Networks in Text	M.	-		bays	engine		contrary to the Chow/Liu	
	in Text Classificat		empirica 1		classif	, longue		algorithm it does not	based on a new method
	ion		evaluati		ier, e	langua		need to compare all variables with each other	
	1011		on of a		Chow	ge text,		so that it saves much	of learning very large
			Bayesia		/Liu	petent		calculations of so-called	tree-like
			n		algorit	databa		DEP-measure. They	Bayesian
			multinet		hm	ses.		estimate also the fitness of	network
			classifie			303.		ETC to the data bye	11000000111
			r based					determining the log	
			on a					likelihood for the	
			new					artificial test and test data.	
			method					The goal was to check the	
			of					quality of the structure of	
			learning					a Bayesian network	
			very					obtained using ETC	
			large					algorithm for various	
			tree-like					DEP functions. Then they	
			Bayesia					compared ETC based	
			n					multi-net classifier	
			network					accuracy with Naive	
			S					Bayes accuracy (NB). On the one hand, though NB	
								is not a particularly good	
								one, it scales quite well	
								for tasks with dozens of	
								thousands of attributes,	
								ETC exhibits a bit higher	
								stability than NB.	
								Standard error values are	
								usually slightly lower	
								than those for NB	
								classifier, though the	
								differences are not	
								striking. It turns out that	
								in spite of the possibility	
								of generation of different trees in case of different	
								sequences of variables the	
								quality of the Bayesian	
								networks obtained is	
								similar they also	
								investigated the	
								complexity of ETC is	
								nlog(N) .then they reduce	
								the ETC complexity, the	
								popular words should be	
								removed from the	
								dictionary. But in some	
-	•	•			•			· *	

the accuracy of the classification.						1 10	
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PROPOSED SYSTEM:

Exiting solution proved to be a good binary classifiers but the text classification is not the binary. The documents contain labels which are not binary in nature. A document might belong to more than one class thus we have to generate algorithm for the purpose of classifying the documents accurately. The solution is divided into two modules. One module handles the English literature part of the document classification. Another module uses Devnagari script for classifying the Marathi documents. English language and one Regional language, in this case MARATHI language, can be used for implementing the text document classification.

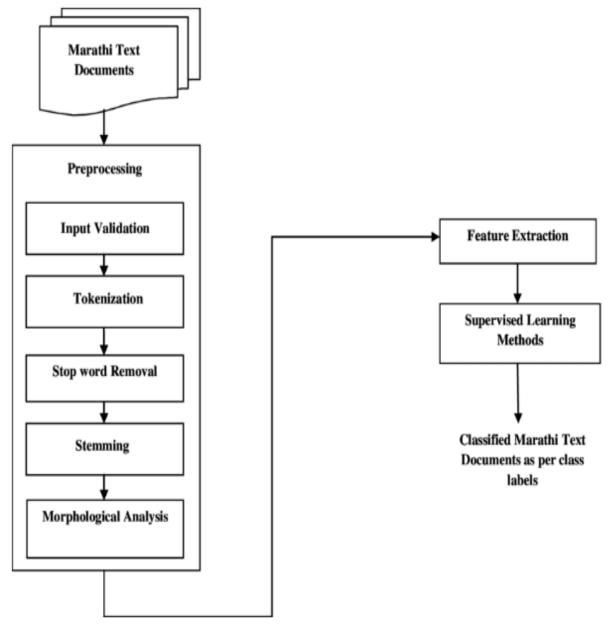
Proposed Model:



1. **Dataset Preparation:** The first step is the Dataset Preparation step which includes the process of loading a dataset and performing basic preprocessing. The dataset is then splitted into train and validation sets.

- 2. **Feature Selection:** The next step is the Feature Selection in which the raw dataset is transformed into flat features which can be used in a machine learning model. This step also includes the process of creating new features from the existing data.
- 3. **Model Training:** The final step is the Model Building step in which a machine learning model is trained on a labelled dataset.

Proposed	Model
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Proposed Architecture

STEPS INVOLVED IN PREPROCESSING:

- Tokenize multi-line comments into single sentences
 - Make a single sentence of a document
 - Store it in new document
- Tokenize each sentence into wordS

- Generates the token for each and every words
- Remove stop words in the tokenized sentence
 - For a selective language, remove all the stop words

• Morphological Analysis:

- Aim to recognize the inner structure of the word
- Morphological analyzer is expected to produce root words for a given input document
- Root and stem of word may differ in their forms
- Lemmatize the words in the tokenized sentence
 - Put the tokenized value instead of word in a sentence to reduce memory consumption

Generate the feature set

• All the remaining words will be used for generating the feature set for the classifier model

• Random Forest:

Random forest builds multiple decision trees and merges them together to get a more and stable prediction. Random Forest also doesn't over-fit the dataset. With variant decision trees, we can obtain different results. The random forest takes the average of the outputs and generalizes the single output with highest number of votes or count.

One of the main feature of random forest is, that it can be used for both classification and regression problems, which form the majority of current machine learning systems. Therefore, in Random Forest, only a random subset of the features is taken into consideration by the algorithm for splitting a node. You can even make trees more random, by additionally using random thresholds for each feature rather than searching for the best possible thresholds (like a normal decision tree does).

Advantages of Random Forest Algorithm:

- The same random forest algorithm or the random forest classifier can use for both classification and the regression task.
- Random forest classifier will handle the missing values.
- When we have more trees in the forest, random forest classifier won't over-fit the model.
- Can model the random forest classifier for categorical values also.

APPENDIX:

EXPERIMENT:

Input: Text documents

Methodology: Support Vector Machine

Output: Category into which Text documents falls

Summary:

- Fully Automated and eliminate the need of manual parameter turing since they can find good parameter settings automatically
- ➤ Document may fall in multiple, one or more categories\
- Each category is treated as separate binary classification
- Max amount of data pre-processing is done for the learning algorithm SVM
- ➤ High dimensionality so doesn't over-fit the data and generalizes accuracy
- Eliminates the need of feature selection, thus avoid high computation overload of text categorization.
- Promising and easy to use algorithm for text categorization

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