A Comparative Study of Sentiment Analysis on Mask-Wearing Practices during the COVID-19 Pandemic

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Abstract

COVID-19 has become one of the most highly orated subject matter in these days. Countries have taken many viable actions to prevent the spread of the virus directed by international recommendations, which led to many disputes concerning wearing a face mask as a preventive measure against the virus. This study aims to assess and compare the overall accuracy, macro precision, macro F-measure and macro recall of the different decision models towards the COVID-19 mask-wearing practices via sentiment analysis. Tweets are labeled and text pre-processing techniques are applied as stemming, normalization, tokenization, and stop-word removal. Subsequently, the tweets are transformed into master feature vectors by applying various feature extraction, feature representation, feature selection and word embedding techniques with five supervised machine learning decision models to predict mask-wearing practices reinforced from Twitter tweets. Moreover, the highest macro F-measure and macro precision are found with feature extraction as hybrid-grams, feature representation as TF-IDF, feature selection as Chi-Squared Test, and highest macro recall with feature extraction as BOW, feature representation as TF-IDF, feature selection as ANOVA F-value. Hence, this study concludes that the Naive Bayes (NB) algorithm outperforms other decision models with master feature vectors applied. In addition, it also outperforms word embedding techniques.

Keywords—COVID-19 pandemic, feature engineering, machine learning, mask-wearing practices, natural language processing, sentiment analysis, supervised decision models.

1 Introduction

THE novel Coronavirus, known as COVID-19, is an emergency respiratory disease that was initially identified in Wuhan, China, on December 19. It is considered to be extremely contagious, and its main symptoms include fatigue, fever, dry cough, dyspnea, and myalgia [1]. It spreads by human to human virus transmission. Hence, distancing from a susceptible population is a better way to control the spread of the COVID-19 [2]. There are plenty of non-pharmaceutical approaches available in protecting from the virus. Hand washing and wearing face masks are ways to keep yourself protected from the virus [3].

Currently, there is no proper vaccine that has been identified for Covid-19. It is considered a severe illness that leads to many deaths and the healthcare systems

being under pressure [4]. Relatively, wearing a face mask helps prevent the virus from transmitting the disease to another healthy person or prevents the illness by reducing the probability of infection. Wearing a face mask has been a controversial topic, and many had a variety of suggestions. However, On April 3, 2020, the CDC (Centers for Disease Control and Prevention) of the US has recommended the public to wear face masks [5]. Mask wearing practices have shown more success and have lessened the virus's threat in the past during the 2003 SARS epidemic [6]. Social media has gained popularity in recent years. It is regularly used among the elderly, teenagers, academics, politicians, and entrepreneurs, irrespective of age or gender. Twitter is one of the commonly used micro-blogging sites among users today. It confines users to tweet within 140 characters. Whereas it allows the users to use a variation of spellings, indecorous use of punctuation marks, slangs, and emojis [7]. This led many researchers to work on sentimental analysis. It is

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a part of natural language processing whose primary focus is on identifying and classifying sentiments or opinions in a textual format. Sentiments can be known as the emotions of service, brand, or campaign in social media platforms. It is a phenomenal way to elaborate the sentiments via comments or situations to understand the surrounding of the brand, service, or campaign [8]. Sentiment analysis has been widely applied in many studies due to the fact that many social media users have their freedom to express their opinions, thoughts, and suggestion for any viral or sensational issue [9]. Hence, it leads to identifying their impression concerning certain topics and current happenings. Understanding whether the given opinion falls into positive or negative sentiment is considered a difficult task. The given features applied in a sentence must contain strong adjectives to classify them. Moreover, sentiment analysis helps to determine the satisfaction of goods or services before they are purchased. Companies and corporations use this information to understand their products and selling patterns [10]. In sentiment analysis, supervised and unsupervised machine learning algorithms play a vital role. Hence, machine learning techniques are used to split the data into test and train. Train data is used to build a classifier to classify the sentiments of given data [10]. If the instances are given as labeled, it falls into the category of supervised learning [11].

The study presented in this paper aspires to achieve three main objectives. Firstly, to compare and contrast the differences in performance measures of five supervised machine learning decision models such as SVM (Support Vector Machine), NB (Naive Bayes), RF (Random Forest), KNN (K-Nearest Neighbour Algorithm), and MaxEnt (Maximum Entropy). Secondly, to evaluate the best feature value representation with feature extraction as BOW (Bag-of-words), N-grams. Whereas, in N-gram, three techniques are compared, i.e., bigram ($N=2$), trigram ($N=3$), and hybrid-grams (BOW + bigram + trigram). In feature representation, Binary Frequency (BR), TF (Term Frequency), TF-IDF (Term Frequency - Inverse Document Frequency), and CountVectorizer are used to convert the text into vectors. Moreover, in feature selection, three techniques are used, i.e. Chi-squared test, information gain, and Anova F-value. Thirdly, feature value representation is compared via Word embedding techniques applying GloVe and Word2Vec embeddings. Hence, the corpus is developed from Twitter tweets by eliminating retweets and tweet duplicates with pre-processing techniques by filtering unwanted symbols, special characters, null values, stop word removal, and correcting misspelled words. Hence,

it is applied in the training model with 1200 tweets labeled as negative and positive, with 600 tweets per each class.

The rest of the paper is organized into the following sections. Related work is discussed in section 2. Section 3 discusses the implementation carried out in the research methodology. Section 4 includes the results. Section 5 is for the discussion of the study. Finally, the conclusion of the study is presented in section 6.

2 Related Work

COVID-19 is a newly transpired disease that is known to be a new research area. However, fewer studies have been conducted in regards to sentiment analysis by the time of piloting this study. Moreover, there have been some studies on sentiment analysis with supervised machine learning algorithms, which to a certain extent, are related to our study.

In Anjaria and Guddeti [12], the authors use Twitter as the primary data collection. Whereas, it is a great platform that intends a quick and effective way in collecting the sentiments. Hence, the sentiment of a sentence is derived by the occurrence of the words which can be positive or negative based on the tone of the words [13]. The study applies several feature extraction techniques to extract the data such as unigram, bigram and (unigram + bigram) hybrid. Hence the results indicate SVM along with the hybrid approach gives a better accuracy compared to NB, MaxEnt, SVM and ANN. The study presents an overview of collecting the tweets, cleaning data and feature extraction to predict the outcome.

Sethi et. al. [14] conduct a study to analyze the emotions of twitter users via tweets related to COVID-19. The proposed model is used to analyze the actual sentiments of the tweets. The dataset for the study is manually created via a twitter API with COVID19 and coronavirus hashtags. Moreover, the study uses MaxEnt, MNB (Multinomial Naive Bayes), decision tree, RF, XGBoost, SVM algorithms with N-gram representations as unigram, bigram and unigram + bigram + trigram. Hence, the study concludes that SVM and decision tree classifier performs better. Although, SVM is considered to be more stable during the experimental process.

Eshan and Hasan [15] pilot a study to detect abusive Bangali text using machine learning algorithms with unigram, bigram and trigram as feature extraction techniques based CountVectorizer and TF-IDF for feature representation. The study uses RF, SVM with Polynomial and Linear kernel, MNB as algorithms. The study finds SVM linear kernel with TF-IDF to

perform better compared to CountVectorizer; albeit, the study does not apply any feature selection techniques.

Comparative research by Mujtaba et al. [16] finds the cause of death (COD) via the autopsy reports. Hence, the study uses unigram, bigram, trigram and hybrid-grams for feature extraction by representing the feature values using BR, TF and TF-IDF. Furthermore, Chi-squared test, information gain and Pearson correlation approaches are used. The study applies five popular decision models, i.e., SVM, J48, RF, NB, KNN to evaluate the performance of each classifier. This study states that SVM performs better than other decision models. Moreover, the study presents a complete methodological structure from data collection to evaluation metrics. Hence, the study confirms the classification accuracy based on several feature value representations.

Samuel et. al. [17] conduct a study on the fear sentiment progression over the peak time of COVID-19 in the United States. The study finds that classification accuracy of 91% for short tweets with the NB decision model and MaxEnt performs similarly well with an accuracy of 74% with short tweets and it also reveals that both models perform weaker in longer tweets. The study applies 4 decision models, i.e., NB, MaxEnt, Linear Regression and K-Nearest Neighbor; albeit the study does not apply any feature selection technique to select the best features from the document of words. Sharma and Daniels [18] conduct a study to execute sentiment analysis based on 2019 election twitter tweets with Word2Vec word embedding along with RF classification model. Moreover, it also improve the accuracy compared to other feature representation schemes, i.e., BOW and TF-IDF. Hence, the study proposes that Word2Vec embedding improves the quality of features, thus it signifies the importance on word embedding in sentiment analysis. However, to the best of our knowledge, there is no existing study related to mask-wearing practices during the Covid-19 pandemic using sentiment analysis.

3 Methodology

The methodology of the study emphasizes the scheme of analyzing the sentiments towards mask-wearing practices during the COVID-19 pandemic. Hence, the study is divided into nine main steps as illustrated in Figure 1. Each step carries certain tasks and it is discussed in the subsequent sections of the methodology. The study uses supervised machine learning decision models to classify with the training and test sets. We have taken 60% dataset for training and the remaining

Fig. 1: Methodology of the Study

for testing. The sentiment for the instance is manually labeled with two categories which helps to create the prediction model. Whereas, the model is accountable to calculate the label for the unlabeled test set.

3.1 Data Collection

This study uses Twitter tweets as the primary data during Covid-19 pandemic which focuses on mask-wearing practices. Whereas, tweets are collected using Twitter API with Python Tweepy Library [19]. We have created a Twitter developer account to extract the tweets via Python Tweepy Library. The gathered 5000 tweets contain a user ID, username, tweet text and tweet location of the tweet posted by the user. Tweets are gathered using the following three main criteria.

- 1) Tweets published during the COVID 19 pandemic are selected for the study.
- 2) Tweets are selected with relevant hashtags and search queries related to mask-wearing practices.
- 3) Tweets are extracted from Twitter API as extended, untruncated Tweet text.

3.2 Data Pre-processing and Data Labeling

The collected twitter tweets are then moved to the pre-processing phase. In this phase, some pre-processing techniques are applied to clean the data found in several retweets from different users. Hence, we keep one tweet and remove the duplicates. Then, unwanted characters, punctuation marks, numerical values are removed. Tweets are then converted into lowercase. Empty or null tweets are removed and misspelled

Fig. 2: Word Cloud Generated after pre-processing

words are corrected with pyspellchecker library [20]. Finally, stop words were filtered from the tweets as shown in Figure 2.

After the pre-processing step, tweets are labeled by applying two classes as positive or negative based on the tweet posted by the user whether they support the mask wearing practices. 1200 tweets are labeled as both positive and negative sentiments as shown in Table 1 which avoids the issue of data imbalance by labeling an equal amount of tweets for each classes.

Sentiment	Labeled Tweets
Positive	600
Negative	600
Total	1200

TABLE 1: Labeled sentiments

3.3 Feature Extraction & Feature Representation

The labeled data is transformed into vectors by applying two feature extraction strategies: i) BOW Representation, and ii) Ngram words representation to apply the sparse data with bigram trigram and hybridgram sequence of words. Scikitlearn provides several vectorizer objects to perform feature extraction strategies efficiently and this study uses four of those vectorizers as,

- 1) **CountVectorizer:** It's one of the basic and simple ways to tokenize a collection of texts into building a known word. It is used to count the number of times a token shows up in the document and uses this value as its weight [21].
- 2) **TF-IDF Vectorizer:** TF-IDF (Term frequency-inverse document frequency) is

used to highlight the words which are more significant to the document in a collection of documents. IDF (Inverse Document Frequency) calculates the importance of a term. Some words which may appear in every document such as 'this', 'the', 'what' and 'if' rank lower because they do not add much significance to the document [22].

- 3) **TF:** It is a feature representation technique used to describe how often a term occurs in a document. Terms are known to be words, phrases or tokens in a text [23].
- 4) **BR:** The binary feature value representation reflects on (i.e., 1 for presence and 0 for absence) features disregarding the occurrence of the term in the document [24].

3.4 Feature Selection

This study then applied several Feature selection Techniques to gather informative features by excluding non-informative features from the sparse feature vector which helps to lessen the feature size. Hence, a large number of features may produce less accurate models and tend to increase computational time and complexity [25]. In this study, three main feature selection techniques are applied to compare and contrast the performance of each decision models. The feature selection techniques are as follows.

- 1) **Chi-Squared Test:** It is a statistical test used to determine whether there is a statistically important difference between expected and observed frequencies in the feature vector [25][26].
- 2) **Information Gain:** It is an entropy-based feature selection method and it is calculated by the use of the term for classification of information by the importance given in a feature vector [27].
- 3) **ANOVA F-Value:** Analysis of Variance (ANOVA) is a statistical way to check the means of two or more different groups in a feature vector. This helps to decrease the features by selecting the important features which significantly improve the computation time and accuracy of decision models [28].

3.5 Decision Models

There are numerous supervised machine learning decision models available for sentiment analysis [29]. However, each decision model has its unique ways of the learning process. Therefore, picking the most

applicable decision model for the study is critical. This study mainly uses five decision models, i.e., linear and polynomial SVM kernels, NB, MaxEnt, RF and KNN applied on master feature vectors to find the best performing decision models.

3.6 Creating Master Feature Vectors

The tweets are pre-processed via the support of Natural Language Tool Kit (NLTK) [30]. After pre-processing the tweets, features are extracted using BOW, N-Grams as bigram, trigram and hybrid-grams (BOW + bigram + trigram). Then, the study advances to the next step by implementing the feature representation by applying BR, TF, TF-IDF and CountVectorizer. Moreover, best 1000 features are filtered using Chi-Squared Test, information gain, and Anova F-Value from the feature vector. Hence, based on the feature extraction, feature representation and feature selection criteria, 48 master feature vector labels are formed as shown in Table 2.

3.7 Applying Word Embedding Techniques

This study applies two word embedding techniques apart from master feature vectors. Whereas, Word2Vec and GloVe allow to show the words in vector form (embedding). Hence, Word2vec embedding is based on training a shallow feed-forward neural network, while GloVe embedding is learnt via matrix factorization techniques [31][32].

4 Results

The experiments show various findings related to each specified portion mentioned in the methodology. The Train and Test accuracy along with macro precision, macro recall and macro F-measure represented with word embedding techniques, master feature vectors indicating 288 analysis with 4 feature extraction, and 4 feature representation accompanying 5 classification algorithms are shown in Table 3-12. The values which are represented in a table with the lowest are highlighted in bold red and the highest with bold green. Moreover, when comparing to the accuracy of train and test for master feature vectors, lowest training accuracy (0.506), test accuracy (0.467) and the highest training accuracy (0.99), and test accuracy (0.842) were obtained. However, in training sets, all algorithms comparatively perform better except KNN which struggles with information gain as the feature selection scheme. Moreover, for word embedding techniques, the lowest train accuracy (0.65), test accuracy (0.581) and the highest training accuracy (1.0), test

accuracy (0.653) are achieved. Therefore, both GloVe and Word2Vec embedding have the highest accuracy when training with NB algorithm.

The performance measurement of master feature Vectors for the lowest macro precision (0.481), macro recall (0.483) and macro F-measure (0.347) were achieved. Whereas, the highest macro precision (0.863), macro recall (0.837) and macro F-measure (0.838) were accomplished by NB algorithm. Overall NB has performed better compared to other five algorithms. In word embedding techniques, lowest macro precision (0.578), macro recall (0.578) and macro F-measure (0.578) were obtained by NB algorithm, and the highest macro precision (0.652), macro recall (0.653) and macro F-measure (0.652) were achieved by linear SVM algorithm.

5 Discussion

This study indicates that hybrid-grams and BOW perform well compared to bigram or trigram when applying Chi-squared test, information gain and Anova F-Value as feature representation. Whereas, NB decision model performs significantly better compared to other algorithms. Moreover, next to NB algorithm, MaxEnt performs better in all feature extraction, feature selection, and feature representation criteria mentioned in the study. Although, it does not perform well in trigram as feature extraction.

When assessing the Chi-squared test, information gain and Anova F-Value, Chi-squared test gives better performance than information gain and Anova F-Value. In terms of feature representation, CountVectorizer comparatively performs well along with other feature representation schemes. This study shows that KNN algorithm does not perform well in all three feature selection techniques compared to other algorithms. Hence, this study finds that the highest macro F-measure and macro precision with feature extraction as hybrid-grams, feature representation as TF-IDF, feature selection as Chi-squared test and the highest macro recall is achieved with feature extraction as BOW, and feature representation as TF-IDF. Feature selection as ANOVA F-value performs better when applying NB as decision model.

This study also uses word embedding techniques to assess the performance of the algorithms. Whereas, linear SVM performs well compared to other algorithms. Although, the highest macro precision, macro recall and macro F-measure values are very low compared to feature vector representation schemes. NB algorithm has the lowest accuracy in both GloVe and Word2Vec word embedding techniques as shown in Figure 3-5 respectively.

Label	Master feature vector	Label	Master feature vector
L1	BOW + BR + Information Gain	L25	Trigram + BR + Chi-Squared Test
L2	BOW + TF + Information Gain	L26	Trigram + TF + Chi-Squared Test
L3	BOW + TF-IDF + Information Gain	L27	Trigram + TF-IDF + Chi-Squared Test
L4	BOW + CountVectorizer+ Information Gain	L28	Trigram + CountVectorizer+ Chi-Squared Test
L5	Bigram + BR + Information Gain	L29	Hybrid-grams + BR + Chi-Squared Test
L6	Bigram + TF + Information Gain	L30	Hybrid-grams + TF + Chi-Squared Test
L7	Bigram + TF-IDF + Information Gain	L31	Hybrid-grams + TF-IDF + Chi-Squared Test
L8	Bigram + CountVectorizer+ Information Gain	L32	Hybrid-grams + CountVectorizer+ Chi-Squared Test
L9	Trigram + BR + Information Gain	L33	BOW + BR + ANOVA F-value
L10	Trigram + TF + Information Gain	L34	BOW + TF + ANOVA F-value
L11	Trigram + TF-IDF + Information Gain	L35	BOW + TF-IDF + ANOVA F-value
L12	Trigram + CountVectorizer + Information Gain	L36	BOW + CountVectorizer + ANOVA F-value
L13	Hybrid-grams + BR + Information Gain	L37	Bigram + BR + ANOVA F-value
L14	Hybrid-grams + TF + Information Gain	L38	Bigram + TF + ANOVA F-value
L15	Hybrid-grams + TF-IDF + Information Gain	L39	Bigram + TF-IDF + ANOVA F-value
L16	Hybrid-grams + CountVectorizer + Information Gain	L40	Bigram + CountVectorizer + ANOVA F-value
L17	BOW + BR + Chi-Squared Test	L41	Trigram + BR + ANOVA F-value
L18	BOW + TF + Chi-Squared Test	L42	Trigram + TF + ANOVA F-value
L19	BOW + TF-IDF + Chi-Squared Test	L43	Trigram + TF-IDF + ANOVA F-value
L20	BOW + CountVectorizer+ Chi-Squared Test	L44	Trigram + CountVectorizer+ ANOVA F-value
L21	Bigram + BR + Chi-Squared Test	L45	Hybrid-grams + BR + ANOVA F-value
L22	Bigram + TF + Chi-Squared Test	L46	Hybrid-grams + TF + ANOVA F-value
L23	Bigram + TF-IDF + Chi-Squared Test	L47	Hybrid-grams + TF-IDF + ANOVA F-value
L24	Bigram + CountVectorizer+ Chi-Squared Test	L48	Hybrid-grams + CountVectorizer+ ANOVA F-value

TABLE 2: Master feature vectors

Fig. 3: Macro recall of 288 analysis + word embedding

Word Embeddings	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
GloVe	0.719	0.702	0.65	1.0	0.714	0.694
Word2Vec	0.761	0.804	0.668	1.0	0.737	0.717

TABLE 3: Train accuracy of word embeddings

Word Embeddings	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
GloVe	0.622	0.6	0.581	0.644	0.628	0.6
Word2Vec	0.653	0.639	0.594	0.603	0.65	0.606

TABLE 4: Test accuracy of word embeddings

Fig. 4: Macro precision of 288 analysis + word embedding

Fig. 5: Macro F-measure of 288 analysis + word embedding

Word Embeddings	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN	Word Embeddings	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
GloVe	0.628	0.604	0.578	0.644	0.632	0.601	GloVe	0.627	0.604	0.578	0.644	0.631	0.588
Word2Vec	0.652	0.638	0.593	0.601	0.65	0.604	Word2Vec	0.653	0.638	0.593	0.601	0.65	0.598

TABLE 5: Macro precision of word embeddings

TABLE 6: Macro recall of word embeddings

6 Conclusion

This study evaluates the mask-wearing practices during the Covid-19 pandemic via analyzing Twitter tweets to find the performance of several decision

models. This study helps to detect whether the mask-wearing practices have been implemented or supported. Hence, those who discourage mask-wearing practices can be prevented based on the sentiment

Word Embeddings	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
GloVe	0.622	0.6	0.578	0.644	0.628	0.58
Word2Vec	0.652	0.638	0.593	0.601	0.649	0.596

TABLE 7: Macro F-measure of all word embeddings

of the tweets. This study has assessed each decision model's performance with 228 master feature vectors by applying several feature extractions, feature representations, and feature selection schemes. Hence, this study concludes that NB performs significantly better, and KNN has the lowest performance compared to other decision models mentioned in the study. This study has two major limitations: i) increasing the number of labeled tweets, ii) applying more classes to the tweets. As the future direction, we can further enhance the study by applying more supervised machine learning algorithms along with different feature representations and feature selection techniques.

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Master Feature Vectors	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
L1	0.927	0.889	0.861	0.831	0.906	0.676
L2	0.827	0.956	0.887	0.876	0.794	0.536
L3	0.865	0.99	0.895	0.887	0.835	0.506
L4	0.938	0.913	0.854	0.86	0.914	0.606
L5	0.863	0.865	0.84	0.736	0.854	0.627
L6	0.757	0.911	0.829	0.763	0.777	0.671
L7	0.76	0.92	0.832	0.756	0.804	0.687
L8	0.849	0.849	0.838	0.731	0.838	0.675
L9	0.811	0.814	0.805	0.67	0.806	0.751
L10	0.621	0.799	0.796	0.714	0.758	0.681
L11	0.579	0.827	0.795	0.729	0.757	0.683
L12	0.796	0.8	0.804	0.694	0.792	0.623
L13	0.92	0.875	0.858	0.815	0.899	0.683
L14	0.775	0.94	0.821	0.887	0.761	0.648
L15	0.77	0.988	0.826	0.876	0.776	0.537
L16	0.921	0.863	0.851	0.827	0.901	0.649
L17	0.927	0.94	0.874	0.842	0.894	0.681
L18	0.821	0.93	0.889	0.845	0.794	0.698
L19	0.867	0.951	0.892	0.819	0.843	0.726
L20	0.921	0.936	0.865	0.833	0.9	0.686
L21	0.868	0.87	0.839	0.717	0.861	0.632
L22	0.802	0.856	0.845	0.749	0.808	0.746
L23	0.756	0.761	0.84	0.752	0.802	0.705
L24	0.87	0.868	0.84	0.721	0.865	0.707
L25	0.811	0.812	0.805	0.676	0.806	0.733
L26	0.651	0.743	0.757	0.67	0.739	0.69
L27	0.651	0.638	0.745	0.673	0.723	0.629
L28	0.81	0.811	0.804	0.706	0.804	0.73
L29	0.923	0.895	0.854	0.805	0.889	0.656
L30	0.781	0.913	0.873	0.807	0.78	0.689
L31	0.802	0.898	0.864	0.789	0.796	0.742
L32	0.924	0.888	0.854	0.81	0.9	0.696
L33	0.942	0.902	0.848	0.826	0.91	0.671
L34	0.814	0.905	0.871	0.845	0.785	0.674
L35	0.855	0.948	0.896	0.856	0.839	0.679
L36	0.936	0.904	0.85	0.837	0.914	0.649
L37	0.877	0.88	0.832	0.727	0.864	0.689
L38	0.781	0.865	0.836	0.73	0.789	0.682
L39	0.731	0.856	0.836	0.756	0.79	0.664
L40	0.875	0.877	0.835	0.768	0.863	0.701
L41	0.821	0.825	0.804	0.724	0.815	0.663
L42	0.59	0.795	0.787	0.679	0.752	0.732
L43	0.567	0.777	0.785	0.682	0.761	0.624
L44	0.820	0.825	0.804	0.730	0.817	0.737
L45	0.932	0.879	0.852	0.830	0.904	0.686
L46	0.731	0.867	0.835	0.829	0.756	0.657
L47	0.796	0.908	0.831	0.832	0.789	0.664
L48	0.927	0.879	0.856	0.813	0.900	0.702

TABLE 8: Train accuracy of 288 master feature vector analysis

Master Feature Vectors	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
L1	0.714	0.719	0.75	0.65	0.742	0.528
L2	0.65	0.642	0.644	0.625	0.636	0.547
L3	0.658	0.631	0.639	0.628	0.636	0.547
L4	0.689	0.656	0.717	0.633	0.711	0.575
L5	0.714	0.714	0.761	0.586	0.742	0.517
L6	0.55	0.581	0.703	0.558	0.581	0.497
L7	0.55	0.647	0.7	0.567	0.597	0.506
L8	0.706	0.697	0.758	0.586	0.728	0.547
L9	0.686	0.672	0.683	0.517	0.692	0.514
L10	0.467	0.506	0.594	0.489	0.494	0.494
L11	0.475	0.506	0.594	0.497	0.494	0.519
L12	0.628	0.606	0.683	0.525	0.639	0.528
L13	0.767	0.731	0.831	0.675	0.772	0.569
L14	0.606	0.617	0.631	0.617	0.614	0.553
L15	0.589	0.628	0.619	0.606	0.611	0.544
L16	0.739	0.681	0.819	0.664	0.753	0.556
L17	0.719	0.703	0.767	0.667	0.739	0.558
L18	0.717	0.728	0.767	0.65	0.689	0.558
L19	0.769	0.75	0.769	0.647	0.728	0.55
L20	0.703	0.683	0.747	0.647	0.728	0.519
L21	0.719	0.708	0.758	0.558	0.731	0.536
L22	0.703	0.703	0.767	0.592	0.697	0.672
L23	0.569	0.564	0.711	0.597	0.642	0.656
L24	0.694	0.708	0.758	0.578	0.722	0.558
L25	0.686	0.678	0.683	0.517	0.689	0.5
L26	0.494	0.553	0.683	0.508	0.561	0.617
L27	0.497	0.481	0.686	0.514	0.542	0.6
L28	0.686	0.681	0.683	0.528	0.692	0.503
L29	0.736	0.731	0.831	0.672	0.783	0.525
L30	0.686	0.719	0.839	0.664	0.686	0.586
L31	0.742	0.8	0.842	0.667	0.736	0.633
L32	0.728	0.708	0.817	0.661	0.758	0.536
L33	0.725	0.694	0.728	0.631	0.733	0.578
L34	0.717	0.736	0.769	0.631	0.697	0.564
L35	0.758	0.744	0.839	0.647	0.731	0.558
L36	0.736	0.708	0.742	0.664	0.739	0.525
L37	0.692	0.683	0.747	0.547	0.708	0.578
L38	0.65	0.694	0.767	0.553	0.681	0.611
L39	0.553	0.728	0.761	0.575	0.669	0.6
L40	0.672	0.678	0.747	0.578	0.708	0.572
L41	0.686	0.675	0.683	0.536	0.689	0.622
L42	0.489	0.667	0.686	0.517	0.6	0.528
L43	0.481	0.581	0.625	0.514	0.542	0.589
L44	0.686	0.678	0.683	0.542	0.692	0.514
L45	0.739	0.736	0.825	0.683	0.778	0.581
L46	0.692	0.742	0.825	0.631	0.667	0.522
L47	0.711	0.772	0.822	0.636	0.692	0.572
L48	0.747	0.711	0.819	0.65	0.778	0.567

TABLE 9: Test accuracy of 288 master feature vector analysis

Master Feature Vectors	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
L1	0.713	0.719	0.8	0.648	0.741	0.518
L2	0.648	0.64	0.643	0.623	0.636	0.604
L3	0.657	0.63	0.637	0.629	0.637	0.77
L4	0.689	0.654	0.728	0.634	0.709	0.55
L5	0.738	0.742	0.822	0.647	0.762	0.549
L6	0.557	0.582	0.725	0.578	0.587	0.488
L7	0.587	0.646	0.715	0.582	0.614	0.498
L8	0.705	0.696	0.82	0.631	0.728	0.541
L9	0.762	0.758	0.797	0.636	0.766	0.564
L10	0.481	0.52	0.606	0.509	0.51	0.481
L11	0.535	0.527	0.603	0.518	0.516	0.506
L12	0.63	0.606	0.797	0.648	0.641	0.526
L13	0.766	0.731	0.858	0.674	0.771	0.571
L14	0.603	0.616	0.63	0.617	0.614	0.553
L15	0.595	0.626	0.617	0.604	0.615	0.645
L16	0.738	0.692	0.843	0.662	0.753	0.558
L17	0.719	0.703	0.788	0.665	0.738	0.554
L18	0.716	0.727	0.797	0.649	0.688	0.553
L19	0.768	0.762	0.794	0.645	0.727	0.565
L20	0.705	0.682	0.781	0.646	0.727	0.51
L21	0.742	0.733	0.816	0.612	0.751	0.525
L22	0.733	0.731	0.817	0.654	0.729	0.698
L23	0.642	0.712	0.778	0.656	0.694	0.693
L24	0.718	0.74	0.816	0.636	0.741	0.554
L25	0.762	0.762	0.797	0.62	0.764	0.535
L26	0.646	0.695	0.783	0.632	0.701	0.666
L27	0.652	0.737	0.785	0.632	0.667	0.75
L28	0.767	0.763	0.797	0.66	0.766	0.546
L29	0.736	0.737	0.858	0.671	0.783	0.51
L30	0.685	0.727	0.861	0.662	0.685	0.586
L31	0.745	0.802	0.863	0.667	0.744	0.636
L32	0.727	0.719	0.844	0.66	0.758	0.526
L33	0.724	0.693	0.769	0.64	0.732	0.6
L34	0.716	0.735	0.798	0.63	0.696	0.56
L35	0.757	0.744	0.839	0.646	0.73	0.562
L36	0.736	0.71	0.778	0.662	0.738	0.51
L37	0.709	0.697	0.794	0.59	0.723	0.592
L38	0.685	0.712	0.821	0.602	0.703	0.612
L39	0.615	0.751	0.818	0.621	0.696	0.603
L40	0.689	0.691	0.794	0.617	0.723	0.58
L41	0.748	0.744	0.783	0.64	0.75	0.726
L42	0.655	0.738	0.785	0.628	0.708	0.587
L43	0.6	0.688	0.741	0.604	0.646	0.712
L44	0.753	0.747	0.783	0.646	0.752	0.585
L45	0.738	0.736	0.854	0.682	0.777	0.58
L46	0.691	0.742	0.849	0.629	0.667	0.527
L47	0.71	0.788	0.848	0.634	0.694	0.584
L48	0.746	0.722	0.851	0.648	0.777	0.563

TABLE 10: Macro precision recall of all 288 master feature vector analysis

Master Feature Vectors	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
L1	0.714	0.716	0.763	0.647	0.74	0.516
L2	0.646	0.64	0.643	0.624	0.636	0.517
L3	0.657	0.631	0.636	0.629	0.637	0.515
L4	0.689	0.654	0.728	0.634	0.709	0.55
L5	0.702	0.701	0.746	0.605	0.731	0.535
L6	0.555	0.582	0.69	0.57	0.586	0.489
L7	0.567	0.646	0.689	0.576	0.606	0.499
L8	0.706	0.696	0.743	0.602	0.729	0.539
L9	0.667	0.651	0.661	0.544	0.673	0.536
L10	0.493	0.517	0.577	0.506	0.508	0.483
L11	0.506	0.521	0.578	0.514	0.512	0.505
L12	0.63	0.606	0.661	0.552	0.641	0.526
L13	0.765	0.726	0.821	0.674	0.77	0.553
L14	0.603	0.616	0.623	0.617	0.615	0.532
L15	0.594	0.624	0.613	0.605	0.615	0.513
L16	0.736	0.67	0.81	0.662	0.75	0.535
L17	0.72	0.698	0.775	0.665	0.738	0.544
L18	0.713	0.727	0.777	0.65	0.689	0.546
L19	0.768	0.756	0.779	0.644	0.728	0.56
L20	0.705	0.705	0.705	0.705	0.705	0.705
L21	0.708	0.696	0.743	0.577	0.719	0.517
L22	0.714	0.713	0.753	0.61	0.708	0.658
L23	0.59	0.59	0.727	0.615	0.657	0.638
L24	0.682	0.695	0.743	0.596	0.711	0.544
L25	0.667	0.657	0.661	0.544	0.67	0.521
L26	0.525	0.579	0.662	0.537	0.587	0.595
L27	0.528	0.513	0.665	0.542	0.568	0.572
L28	0.666	0.66	0.661	0.555	0.673	0.525
L29	0.733	0.723	0.821	0.671	0.782	0.507
L30	0.685	0.711	0.83	0.66	0.686	0.573
L31	0.745	0.796	0.833	0.66	0.741	0.624
L32	0.726	0.699	0.807	0.657	0.756	0.52
L33	0.725	0.692	0.74	0.637	0.733	0.556
L34	0.713	0.734	0.779	0.631	0.697	0.558
L35	0.757	0.745	0.837	0.647	0.731	0.561
L36	0.737	0.711	0.753	0.662	0.739	0.507
L37	0.7	0.69	0.733	0.565	0.716	0.558
L38	0.663	0.703	0.752	0.571	0.69	0.6
L39	0.573	0.716	0.746	0.592	0.68	0.587
L40	0.68	0.685	0.733	0.593	0.716	0.553
L41	0.668	0.656	0.662	0.561	0.671	0.597
L42	0.52	0.647	0.665	0.544	0.622	0.55
L43	0.512	0.603	0.647	0.54	0.567	0.561
L44	0.667	0.658	0.662	0.567	0.674	0.539
L45	0.737	0.733	0.815	0.68	0.776	0.568
L46	0.688	0.738	0.816	0.628	0.668	0.526
L47	0.711	0.763	0.813	0.632	0.694	0.58
L48	0.746	0.702	0.809	0.647	0.776	0.554

TABLE 11: Macro recall of all 288 master feature vector analysis

Master Feature Vectors	SVM Linear	SVM Polynomial	NB	RF	MaxEnt	KNN
L1	0.713	0.717	0.745	0.647	0.74	0.505
L2	0.646	0.64	0.643	0.623	0.635	0.403
L3	0.657	0.63	0.636	0.628	0.636	0.38
L4	0.688	0.654	0.713	0.633	0.71	0.49
L5	0.698	0.696	0.741	0.562	0.73	0.487
L6	0.549	0.58	0.686	0.551	0.58	0.484
L7	0.529	0.646	0.686	0.562	0.593	0.496
L8	0.705	0.696	0.738	0.568	0.728	0.535
L9	0.646	0.625	0.632	0.436	0.654	0.467
L10	0.387	0.495	0.556	0.461	0.479	0.472
L11	0.359	0.485	0.561	0.473	0.467	0.487
L12	0.628	0.605	0.632	0.45	0.639	0.526
L13	0.765	0.727	0.824	0.674	0.771	0.531
L14	0.603	0.616	0.622	0.616	0.614	0.489
L15	0.588	0.624	0.613	0.604	0.611	0.383
L16	0.737	0.666	0.813	0.662	0.75	0.494
L17	0.719	0.698	0.765	0.665	0.738	0.527
L18	0.714	0.727	0.764	0.649	0.688	0.536
L19	0.768	0.75	0.768	0.644	0.727	0.544
L20	0.703	0.682	0.744	0.646	0.727	0.5
L21	0.704	0.691	0.739	0.53	0.718	0.483
L22	0.699	0.699	0.75	0.568	0.693	0.648
L23	0.536	0.504	0.701	0.576	0.629	0.621
L24	0.676	0.688	0.739	0.552	0.709	0.527
L25	0.646	0.633	0.632	0.442	0.65	0.456
L26	0.385	0.489	0.636	0.419	0.502	0.559
L27	0.39	0.347	0.64	0.432	0.477	0.495
L28	0.645	0.637	0.632	0.452	0.654	0.453
L29	0.733	0.724	0.824	0.671	0.782	0.475
L30	0.685	0.711	0.833	0.661	0.685	0.563
L31	0.742	0.798	0.836	0.66	0.736	0.621
L32	0.726	0.698	0.809	0.657	0.757	0.498
L33	0.724	0.693	0.723	0.63	0.732	0.512
L34	0.714	0.734	0.767	0.63	0.697	0.558
L35	0.757	0.744	0.838	0.646	0.73	0.558
L36	0.736	0.708	0.738	0.662	0.738	0.477
L37	0.69	0.682	0.728	0.522	0.707	0.523
L38	0.643	0.693	0.749	0.525	0.678	0.595
L39	0.518	0.714	0.742	0.555	0.665	0.577
L40	0.67	0.677	0.728	0.561	0.707	0.523
L41	0.65	0.634	0.636	0.475	0.654	0.545
L42	0.371	0.622	0.64	0.439	0.564	0.483
L43	0.359	0.538	0.593	0.442	0.483	0.481
L44	0.649	0.638	0.636	0.483	0.658	0.452
L45	0.737	0.733	0.817	0.68	0.776	0.557
L46	0.689	0.739	0.818	0.628	0.666	0.522
L47	0.71	0.764	0.815	0.633	0.692	0.57
L48	0.746	0.7	0.811	0.647	0.777	0.544

TABLE 12: Macro F-measure of all 288 master feature vector analysis

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