What topics and Emotions Expressed by Glaucoma Patients? A Sentiment Analysis Perspective

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Abstract

The recognition of eye disorders has the potential to reduce blindness in people. The need for a procedural method is important to boost the overall recognition process. Although the identification of certain disease symptoms is crucial to an early diagnosis, this study proposed a novel procedural mechanism to predict eye diseases on Twitter platform (Twitter) using users' sentiments embedded in their social media data. Glaucoma was investigated as one example of various eye diseases. Themes related to glaucoma were extracted using Latent Dirichlet Allocation (LDA). Subsequently, association rules mining is employed to identify disease-related symptoms within each theme. Our methodology also incorporates semi-supervised learning, utilizing the innovative "Yet Another Two-Stage Idea" (YATSI) algorithm, to recognize glaucoma based on individuals' tweets. Our results showed that certain emotions, such as fear and sadness emotions, were highly associated with glaucoma messages. The findings revealed that emotion-related features have a significant impact on improving the prediction process of glaucoma in patients. As a result, this study proposed a low-cost procedural mechanism for the early-stage detection of eye disorders using microblogs data. The proposed method improves the decision-making process via users' sentiment embedded in the data.

Keywords: social media mining; glaucoma recognition; machine learning; decision-making

1. Introduction

Eye diseases affect people of different age groups and conditions. Past reviews of the literature have indicated the importance of preventing certain eye diseases at an early stage. For example, Prokofyeva and Zrenner (2012) reviewed previous studies on the main eye diseases leading to blindness in

Europe. The review found that certain diseases, such as age-related macular degeneration, diabetic retinopathy, and glaucoma, can be commonly found in Europe. The association between eye diseases and other health conditions has been reported in many previous studies (e.g., (Kuźma et al., 2021; Kyari, Adekoya, Abdull, Mohammed, & Garba, 2018). In addition, the relationship between glaucoma and individual emotional status was reported by Stamatiou, Kazantzis, Theodossiadis, and Chatziralli (2021). The authors identified a change in patients' emotional state when developing glaucoma. Changes in people's emotions are usually expressed in different forms. Given that social media platforms are the new means for communication and expressing our emotions (Sarsam & Al-Samarraie, 2021b; Sarsam, Al-Samarraie, Alzahrani, Alnumay, & Smith, 2021), we can use them to predict eye diseases in their early stages.

Glaucoma is defined as one of the main causes of visual impairment globally (Tucker, 1993). It is characterized by certain features that are broadly shared among patients, including an intraocular and high pressure, cupping of the optic nerve head and visual field loss. Since there is no cure or possible corrections in case of blindness, the potential for glaucoma prevention warrants further investigation. Thus, this study attempts to answer one key question of 'How to predict eye-diseases within a specific time span?' To answer this question, we used users' emotions in the form of tweets to examine their polarity and to find disease-related topics needed for building the prediction model. In addition, we used an image classification technique to assess the prediction quality of our text classification approach. For this purpose, two phases were established; the first phase was designed to select the best image classification algorithm to perform the recognition process of Glaucoma from fundus images collected from social media. The second phase was designed to examine the consistency level of predictions between text classification and image classification using newly collected data. The following section discusses previous studies on disease prediction from social media sites.

2. Literature Review

Studying how changes in people's emotions can be used to infer certain needs or preferences is attracting more attention recently. Sentiment analysis has been used in many health studies to examine people's decisions through their emotions. This can be due to its role in processing and characterizing a wide range of opinions in a short period of time. In addition, the traditional method for extracting and examining public's emotions requires a large-scale survey, which is not always possible (S. Yu, Eisenman, & Han, 2021). Social media sites provide the means for users to express and share their opinions online. Twitter is one example of social media platforms that allow researchers extract and process tweets on certain topics (Kessler & Schmidt-Weitmann, 2021). This encouraged many researchers to consider its use in predicting various health-related topics. For example, Yadav, Ekbal, Saha, and Bhattacharyya (2018) discussed the potential of using online forums to extract and analyze users' health sentiments. The authors examined a deep Convolutional Neural Network (CNN) based medical sentiment analysis system for the identification of multiple medical conditions in relation to specific users' treatment. Carchiolo, Longheu, and Malgeri (2015) used the sentiment features posted on Twitter to extract information about diseases with spatio-temporal constraints. The authors proposed SNOMED-CT in an attempt to detect medical terms. Pradeepa et al. (2020) developed a machine learning approach to detect sufferers with mental illness by using posts collected from mental health communities in Reddit.

Another stream of studies used social media sources to predict various health conditions and diseases. Social media sites offer a rich source of information that can be tracked and studied at different time scales. Twitter is one popular example of social media sites that is commonly used by people to share information, debate topics, and communicate with others (Al-Samarraie, Bello, Alzahrani, Smith, & Emele, 2021). Many previous studies have used Twitter as a way to extract and study changes in users' emotions based on observations of different posts (Santhosh Baboo & Amirthapriya, 2022). However, this process can be time consuming and not effective when the data size is large or data arrive sequentially over time (Balakrishnan, Khan, & Arabnia, 2020). This motivated several studies to explore the potential relationship between users' emotions and their eye diseases. For example, a study by Mullins et al. (2017) found specific types of emotions (fear, anger, and sadness) using 2,641 tweets on dry eye disease (DED). The authors reported the feasibility of using social media platforms in understanding patients' experience and struggle with the disease, which is an informative mechanism to diagnose the disease. In the same context, Cook et al. (2019) used social media platforms to assess patients' experience of living with DED using the natural language processing (NLP) approach. The authors found that most DED patients shared information about their disease symptoms, causes, diagnosis, and treatments on social media platforms. The posted DED-related information was found to represent specific emotions through patients' experience with the disease.

Other recent studies (e.g., Sarsam and Al-Samarraie, 2021) explored the possibility of detecting glaucoma disease on microblogs. The authors collected tweets that discussed glaucoma and grouped them using a hierarchical clustering algorithm. Then, in each cluster, the co-occurrence analysis was applied to map specific disease-related terminologies. The authors extracted users' emotions (anger, fear, sadness, and joy) and polarity (positive, neutral, and negative) from the tweets to identify the emotion type that is related to glaucoma. They then used these emotions to detect the disease via multinomial logistic regression. The findings of their work revealed that negative, fear, and sadness emotions can be useful in the detection of glaucoma from social media data. Based on these, it can be said that previous studies offered some insights about the possibility of predicting eye diseases by characterizing patients' stories in their social media posts. In addition, emotions can be a good indication of peoples' lifestyles, disease symptoms, pain and recovery. All this information can enable us to better predict the health status of patients and build a patient-centric model of eye diseases with application to health decision-making and eye disease detection.

Despite these efforts on eye disease detection, the literature showed limited evidence in relation to the use of patients' emotions shared on specific social media platforms in detecting Glaucoma. For example, L. Li, M. Xu, X. Wang, L. Jiang, and H. Liu (2019) proposed an attention-based CNN for glaucoma detection (AG-CNN). The authors collected a large database of glaucoma images that were labeled with either positive glaucoma or negative glaucoma. The authors also developed a prediction mechanism of AG-CNN. The results demonstrated a great potential for the detection of AG glaucoma disease. Maetschke et al. (2019) developed a detection mechanism to classify eyes as healthy or glaucomatous. The authors used deep learning technique using 3D CNN. Based on these observations, it can be assumed that social media platforms can be used to offer a good source of information for understanding changes in their health conditions through emotions. Therefore, this study developed a procedural approach predicting glaucoma on microblogs. In this sense, we extracted and grouped glaucoma-related tweets across a specific time period. The following section explains the method of this study.

3. Method

Figure 1 shows the process of implementing the proposed mechanism of using text classification to recognize glaucoma form from individuals' tweets. The process includes data collection, data pre-processing, topic modeling, Part-of-speech tagging, association rules mining, emotion extraction, and glaucoma recognition. Then, image classification technique was used via YATSI to evaluate the proposed approach. These stages are outlined in detail in the following sections.

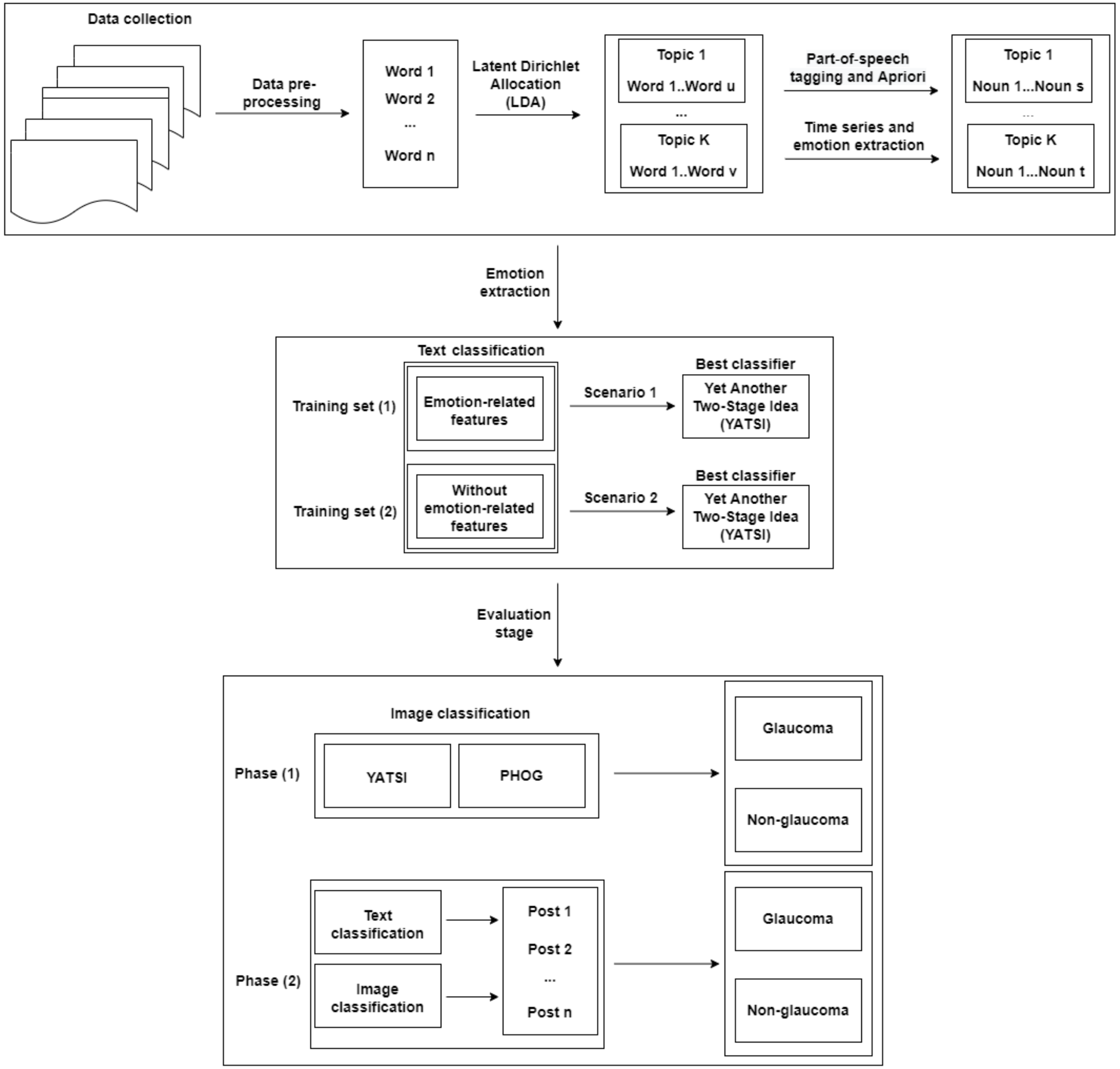


Figure 1: The performed process

3.1 Data collection

A total of 3,705,486 English tweets were collected within six months (November 1st, 2019, till 30th April 2020) using the Twitter free streaming Application Programming Interface (API). For this purpose, several search keywords were used, including ‘eye disorder’, ‘glaucoma’, ‘eye strain’, ‘refractive errors’, ‘watery eye’, ‘night blindness’, ‘dry eye syndrome’, ‘diabetic retinopathy’, ‘conjunctivitis’, and ‘eye allergy’. In order to produce a reliable analytical result, the collected tweets were prepared via different data preparation tools.

3.2 Data pre-processing

Several data preparation tools were applied to produce reliable data. First, data transformation was applied using the tokenization method to extract data features and building the dictionary (Sarsam, Al-Samarraie, & Al-Sadi, 2020). In this sense, the n-gram tokenizer method was implemented to extract the text-related features from each tweet such as character unigram and character bigram. We also removed all punctuation and numbers along with the hashtags to ensure effective mining of the data. This includes special characters and terms with less than three characters. Second, all the extracted features were converted into a lowercase form where some of the unnecessary words were deleted using the stop-words list method where 32.11% of stop words were identified. Lastly, the length of the tweets was normalized using the L2 norm. The process of normalizing the collected tweets was based on the minimization of the sum of the squares of the residuals (Inal, Yetkin, Bulbul, & Bilgen, 2018).

3.3 Topic modeling

After having our data prepared, the Latent Dirichlet Allocation (LDA) algorithm was used to extract the hidden topics from the data (Logan, LaCasse, Lunday, & Mining, 2023; Sievert & Shirley, 2014). LDA is an unsupervised generative probabilistic technique that is used to model the collection of documents. The technique displays the documents as random mixtures over latent topics where a topic is described by a distribution over the text-related features. LDA assumes that each document can be represented as a probabilistic distribution over underlying topics where topic distribution in all documents has a common Dirichlet prior. The pseudocode for all the utilized LDA algorithm is provided in the "Technical Information" document accompanying the manuscript.

3.4 Part-of-speech tagging

In this study, the part-of-speech (POS) tagging technique was applied in each theme to mine the essential features related to it following the recommendation of Qi, Shabrina, and Mining (2023). Part-of-speech tagging is a popular method to extract different parts of speech from a text (Wang, Meng, Wang, Chen, & Liu, 2021) by assigning a unique tag to the extracted term. Therefore, we applied POS using the Penn State Treebank tokenizer in conjunction with the Document Pre-processor approach. Then, the Penn State Treebank tokenizer was utilized again to produce relevant words before applying the Probabilistic context-free grammar parser (Sarsam et al., 2020). This process enabled us to extract the 'noun' words from the sentence that were analyzed using the association rules mining technique.

3.5 Association rules mining

To extract the glaucoma-related symptoms, the Apriori algorithm (Liao, Yang, & Mining, 2021) was applied where the delta value was set at 0.05

to reduce the support until reaching its minimum value. In addition, we set the minimum metric score was set at 0.9 as well as both upper and lower bounds of the support were set at 1.0 (Sarsam & Al-Samarraie, 2021a). After extracting disease-related symptoms, time series technique was employed to examine the periodical changes in these symptoms to further understand the glaucoma terminological behavior. See the "Technical Information" document for the Apriori algorithm's pseudocode.

3.6 Emotion extraction

At this stage, users' emotions were extracted from their tweets in each topic using NRC Affect Intensity Lexicon (Mohammad, 2017; Nandwani, Verma, & mining, 2021). The NRC consists of a list of English words and their associations that were used to represent four basic emotions (anger, fear, sadness, and joy). According to Mohammad (2017), for a given word and emotion X, the scores range from 0 to 1 where a score of 1 indicates that it carries the highest amount of emotion X, while 0 score tells that the word conveys the lowest amount of the X emotion. Finally, the emotions for each tweet were computed by adding the relevant associations of the words for a certain lexicon.

3.5 Glaucoma recognition using text classification

At this stage, the semi-supervised learning technique was used for glaucoma recognition because it utilizes both labelled and unlabeled data, which is advantageous when dealing with large datasets where labelled instances are scarce (Abbas & Mining, 2021). To assess the efficiency of the extracted emotions, we performed the classification technique via a training set with and without emotion-related features. In this sense, two machine learning algorithms were compared to find the best prediction scheme for this detection task. These algorithms are: "Yet Another Two-Stage Idea" algorithm or

“YATSI” and “Learning with Local and Global Consistency” or “LLGC” (refer to the "Technical Information" document for the pseudocode of the two algorithms). “YATSI” developed by Driessens, Reutemann, Pfahringer, and Leschi (2006). This algorithm is based on the Random Forest model. We used YATSI due to its high capability in improving the predictive performance of the base classifier (Driessens et al., 2006; Imam, Issac, & Jacob, 2019). It works in two stages where a supervised classifier (random forest) is trained on the available training data, at the first stage. Then, at the second stage, the resulting model is utilized to pre-label all the test set instances. After that, these pre-labeled instances were used together with the original training data using a weighted nearest neighbor technique. The weights generated from the nearest neighbor classifier were used to help us limit the level of trust of the algorithm during the labeling process of the model from the first step. The default value given to the weights of the training data was 1.0, whereas the weights of the pre-labeled test-data was N/M (N represents the number of training examples and M represents the number of test-examples) (Driessens et al., 2006).

This study also used an LLGC graph-based approach to solve the semi-supervised learning problem by satisfying both the local and global consistency assumptions. For example, let the dataset $\boldsymbol{\mathcal{X}} = \{x_1, \ldots, x_l, x_{l+1}, \ldots, x_n\} \subset \mathbb{R}^m$ and a label set $\boldsymbol{\mathcal{L}} = \{1, \ldots, c\}$, the first l points x_i $(i \leq l)$ are labeled as $y_i \in \boldsymbol{\mathcal{L}}$ and the points x_u $(l + 1 \leq u \leq n)$ are unlabeled. F refers to the set of $n \times c$ matrices of nonnegative entries. A matrix $F = [F_1^T, \ldots F_n^T]^T \in \boldsymbol{\mathcal{F}}$ refers to classifying the dataset by labeling each instance as x_i *as* label $y_i = \mathrm{argmax}_{j \leq c} F_{ij}$ (F is the vectorial function F: $\boldsymbol{\mathcal{X}} \rightarrow \mathbb{R}^c$ that assigns vector F_i to each point x_i). The same matrix is also used to determine the $n \times c$ matrix $Y \in \boldsymbol{\mathcal{F}}$ with $Y_{ij} = 1$ if x_i *is labeled as* $y_i = j$ and $Y_{ij} = 0$ otherwise. Finally, W refers to the affinity matrix W.

The weight matrix W of G is normalized symmetrically to convergence of the following iteration. This step is mandatory to assure the convergence of the iteration. During each iteration, each instance receives the information from its nearby instances. The parameter α denotes the relative amount of the information from the nearest instances and the initial class information of each instance. The information is spread symmetrically because S is a symmetric matrix. Finally, the algorithm sets the class of each unlabeled specimen to the class of which it has received most information during the iteration process.

Both YATSI and LLGC were applied for two times on the training set where at the first run time, these algorithms classified data without emotional features, while at second run time, the algorithms invoked on the data that comprise users' emotions.

In this study, the machine learning algorithms were implemented via the Weka platform (Waikato Environment for Knowledge Analysis) using a stratified tenfold cross-validation technique. To select the best predictive model, we relied on several evaluation metrics, including Accuracy, Kappa statistic, and Confusion matrix.

3.6 Evaluation stage: Glaucoma recognition using image classification

The evaluation stage was divided into two phases. The first phase consisted of selecting the best image classification algorithm to be used for Glaucoma recognition. We compared the prediction results of YATSI and LLGC methods on 859 "non-glaucoma" and 859 "Glaucoma" digital fundus images. These two algorithms were trained on two types of image-related features that we extracted via the "Pyramid Histogram of Oriented" method or "PHOG" (Pathan et al., 2021) and Gabor filter (Xu & Fan, 2022). Section 4.5 provides more information about the process of selecting the best recognition algorithm for Glaucoma images. The second phase consisted of determining the consistency level of the predictions between text classification and image classification, which was accomplished using newly collected data (validation dataset). To do so, we randomly collected 2000 posts with each post containing both text and fundus images. Then, for each post, we labeled the text and images as "Non-glaucoma" or "Glaucoma" using our text classification approach described above. Finally, kappa statistic was used to measure the agreement between the two labels of each post.

4. Results

4.1 Topic modeling and association rules result

Figure 2 depicts the LDA results. Based on the figure, each circle refers to a specific topic in our data, whereas the size of the circle refers to the frequency of a particular topic. Moreover, the distance between the circles indicates the similarity between the topics. In this figure, we can see that LDA extracted two main themes. The first theme contains glaucoma-related topics where people mainly discussed glaucoma symptoms, including getting the blurred vision, headache, halos, eye pain, and eye redness. For each of the discussed topics, people shared their feelings and expressed their opinion towards the medication that has been used. The second theme contained topics related to the general eye allergy caused by pollen, dust mites, mold, or pet dander. Also, the topics discussed eyewear allergy caused by its manufacturing materials like plastics, rubber, solvents, and waxes. In addition, solutions for the eyewear allergy have been discussed in this theme, including the discontinuity of wearing such glasses as well as using stainless steel glasses if a person has an allergy towards the nickel material.

After extracting these topics, we asked three ophthalmologists (with 14 years of experience) to help us providing valid data labels. The ophthalmologists suggested labeling the first topic as "Glaucoma-related topics" and the second topic as "Allergy-related topics" (non-glaucoma).

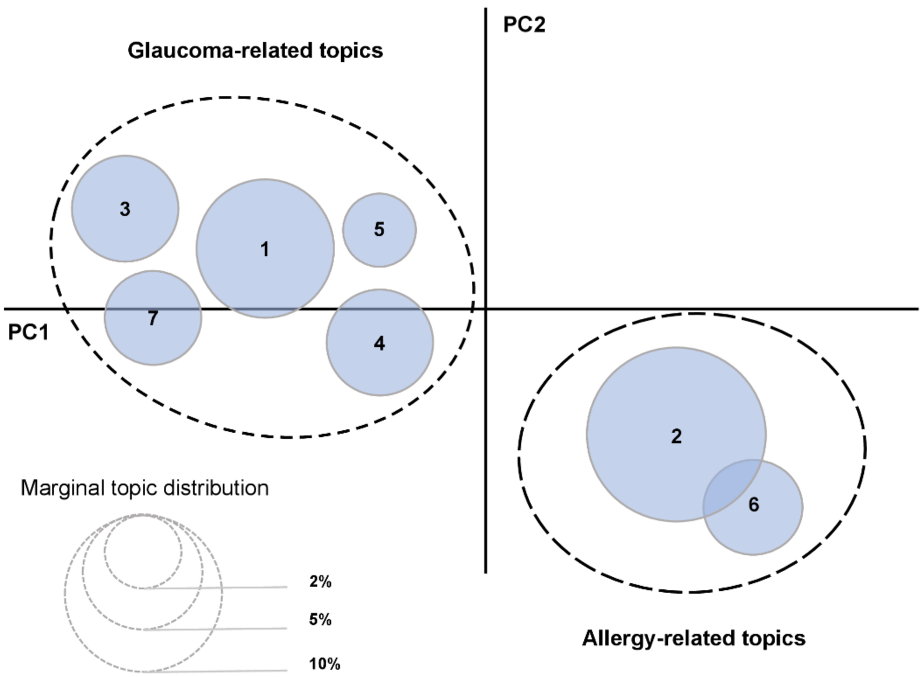


Figure 2: The results of the LDA algorithm

The Apriori results are summarized in Figure 3. From the figure, the observations distinctly showed that the terms headache, blurred vision, halos, eye redness, eye pain were highly associated with the glaucoma disease (Figure 3a) in which their confidence values were 95 %, 92 %, 94 %, 96 %, 98 %, and 99 % for each of these terms, respectively. On the other hand, the association rule results revealed terms like itchy eyes, tears, burning, swollen eyelids, and irritated eyes. These topics were highly associated with allergy-related topics (Figure 3b) with confidence values 92%, 91%, 96%, 99%, and 97%, respectively.

To understand the changes of the extracted terms during the data collection period, time series technique was used. The result of time series showed that an increase in the frequency of glaucoma terms (headache, blurred vision, halos, eye redness, and eye pain) during the search period. However, allergy-related terms showed random behavior with a clear decline for each of these lines indicating the reduction in tweets number (see Figure 4).

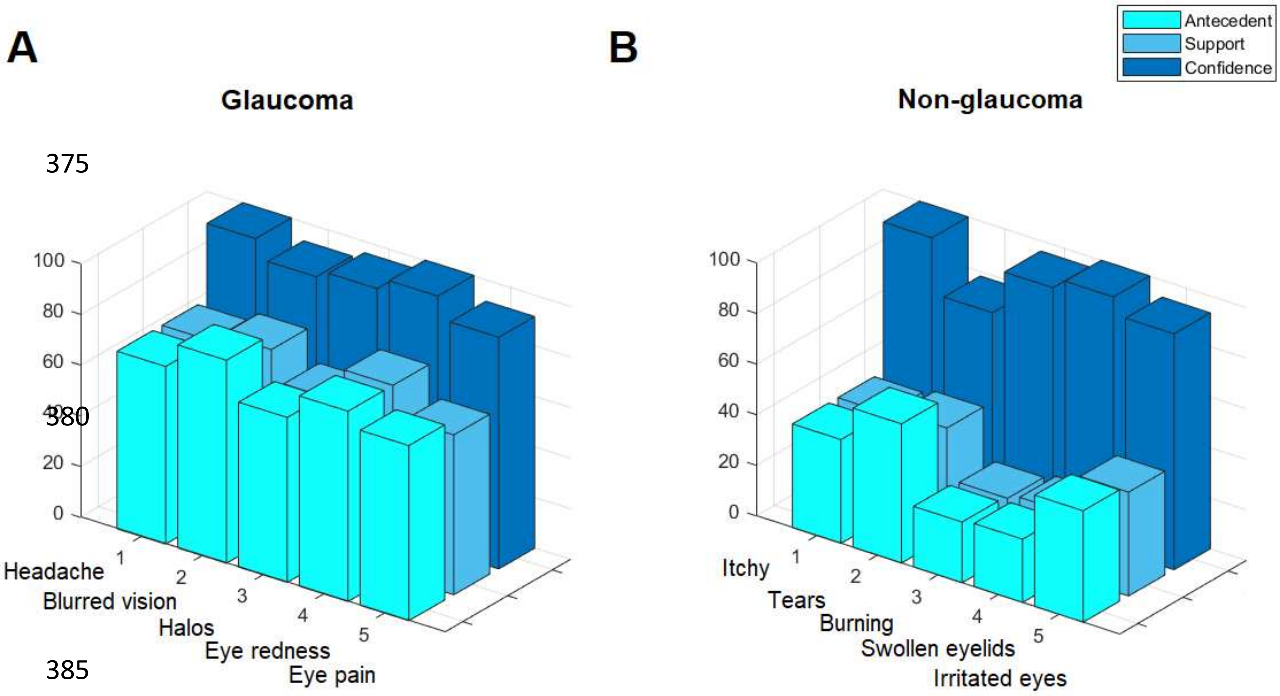
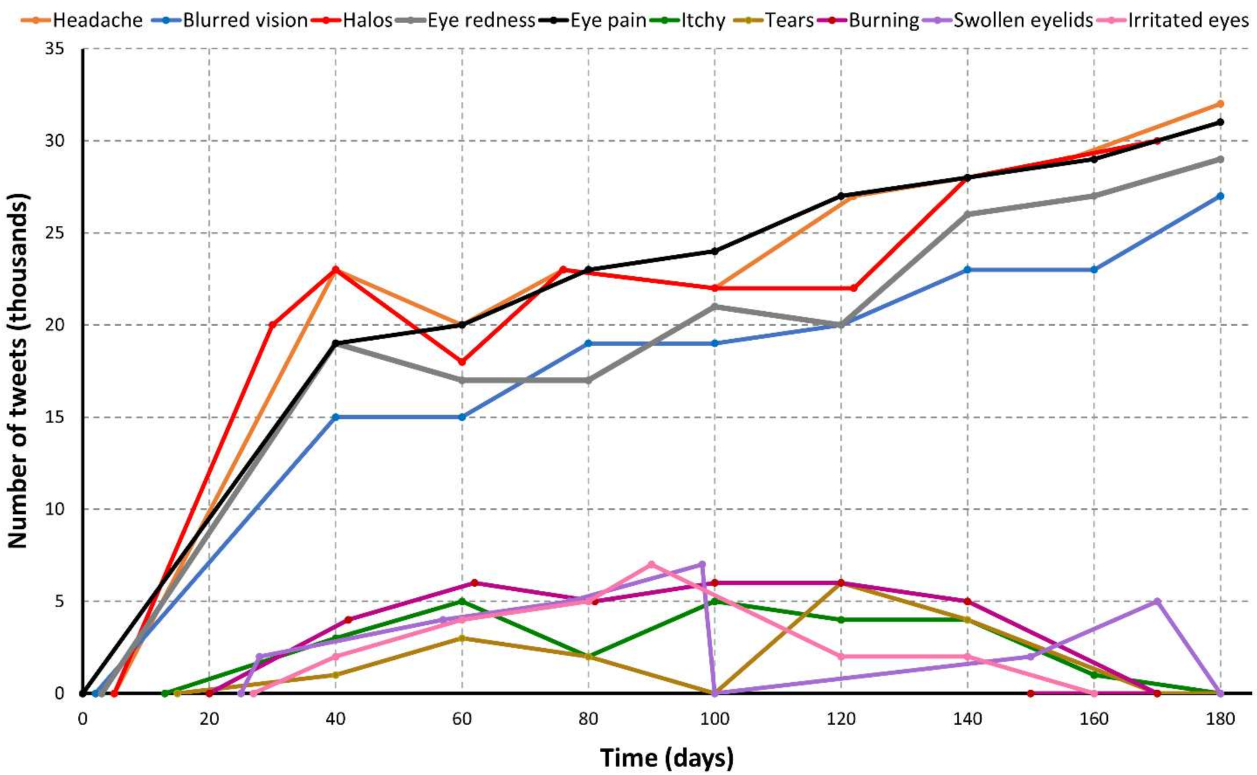


Figure 3: The Results of the Apriori algorithm



390 Figure 4: Time series results

4.2 Emotion extraction results

Figure 5 depicts the results of NRC Affect Intensity Lexicon where the ‘Glaucoma’ group contained three dominant emotions: anger (9%), fear (75%), and sadness (16%). However, anger (10%), sadness (8%), and joy (82%) were found to be the dominant emotions for the ‘non-glaucoma’ group. The extracted emotions were added to the data and used by the machine learning algorithms in the classification task.

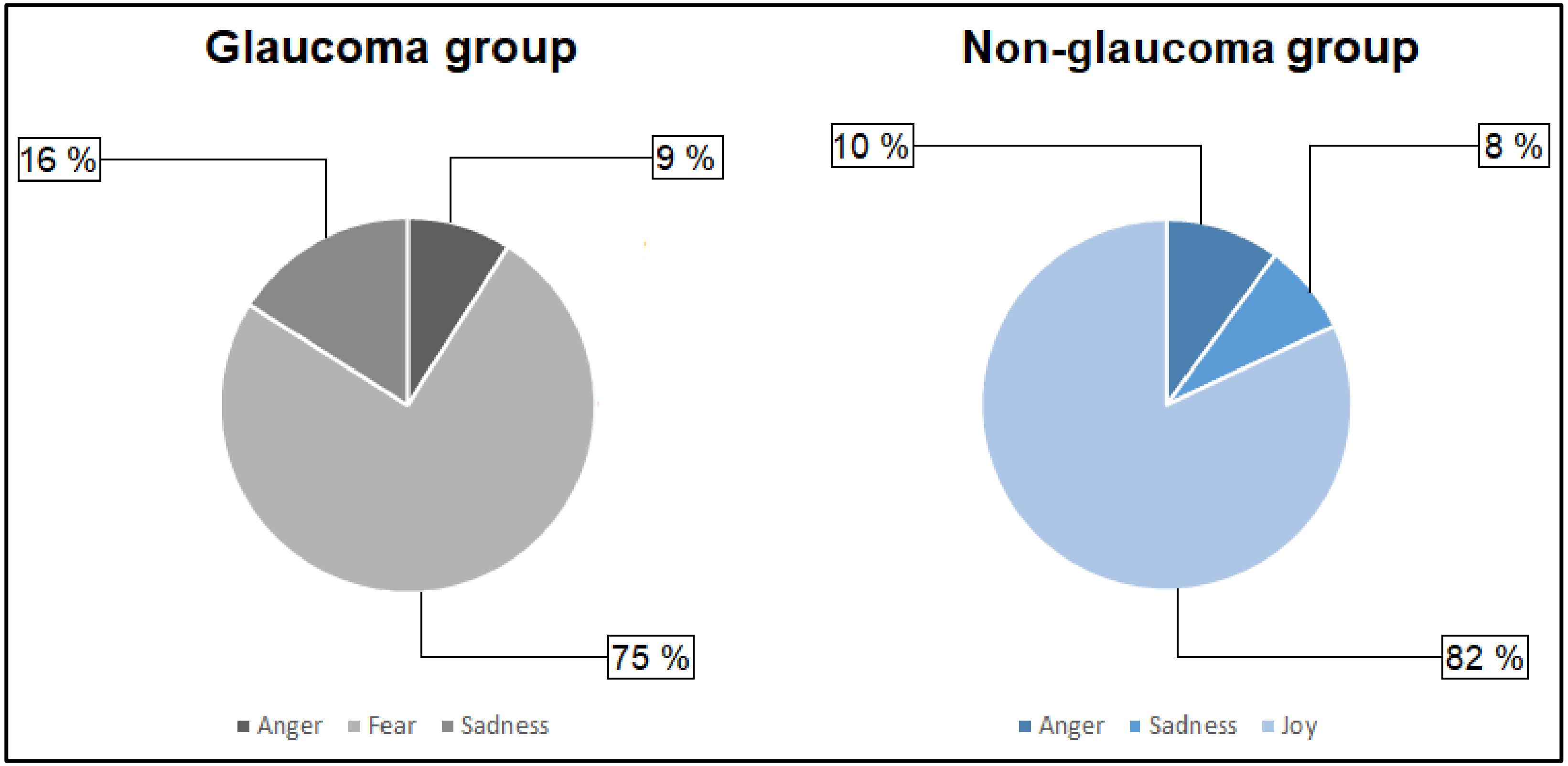


Figure 5: The extracted emotions in the two groups

4.3 Classification results

The classification results of YATSI and LLGC algorithms are summarized in Table 1. From this table, results indicated that YATSI has (without using emotion features) a higher accuracy value (58.13%) than LLGC (49.46%). Also, YATSI method scored a higher kappa statistic (66.31%) compared with LLGC (57%). In contrast, LLGC had a higher RMSE result (94%) than YATSI classifier (86%). On the other hand, using emotion-related features, YATSI achieved a higher accuracy (98.91%) and kappa statistic (97%) than LLGC's accuracy (81.79%) and kappa statistic (85%) values. Nevertheless, LLGC scored a higher RMSE value (12%) than YATSI method (3%). Figure 6 summarizes the evaluation results of the classification process. As a result, emotion-related features boosted the prediction capability of both YATSI and LLGC methods. In light of that, YATSI can efficiently detect glaucoma disease from the Twitter data.

Table 1: Classification results

Algorithm	**Emotion**	**Accuracy (%)**	**Kappa statistic (%)**	**RMSE (%)**
YATSI	Without	58.13	66.31	86
	With	98.91	97	3
LLGC	Without	49.46	57	94
	With	81.79	85	12

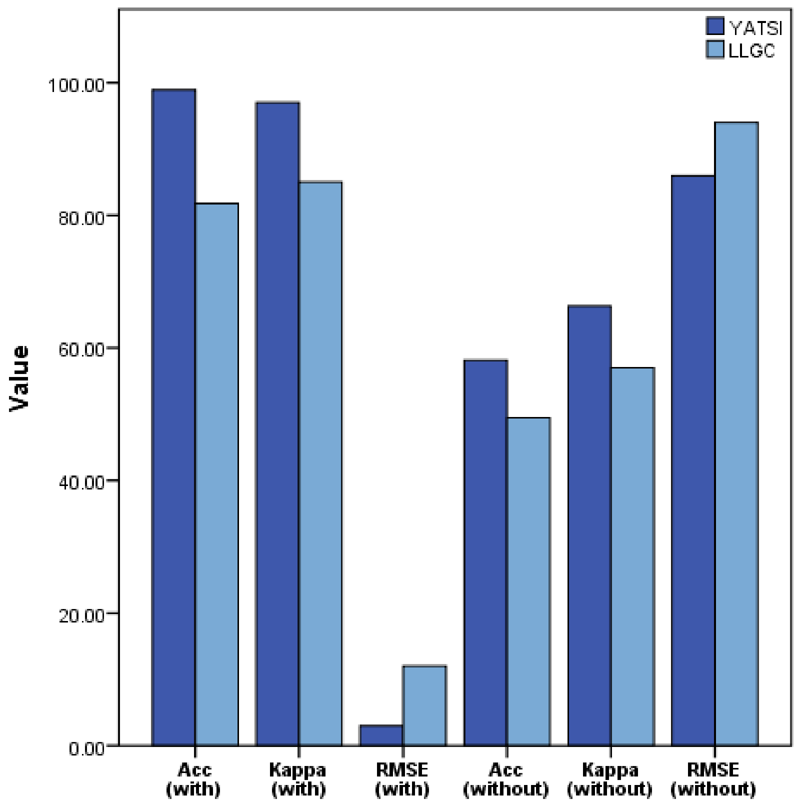


Figure 6: Evaluation metrics of the three algorithms

4.4 A comparison of the proposed approach with previous studies

To evaluate the robustness of the proposed mechanism, we compared our results with relevant studies from the literature. The comparison result revealed that our heuristic mechanism outperformed the previous techniques (see Table 2).

Table 2: Glaucoma recognition techniques utilized in the literature

	Study	Approach	Result (%)
1.	Li, Xu, Wang, Jiang, and Liu (2019)	Attention-based CNN for glaucoma detection (AG-CNN)	Accuracy = 95.3 %
2.	Maetschke et al. (2019)	3D Convolutional Neural Network (CNN)	Accuracy = 94 %
3.	Ahn et al. (2018)	Simple logistic classification and convolutional neural network via Tensorflow	Accuracy = 95 %
4.	Kim, Cho, and Oh (2017)	Random forest	Accuracy = 97 %
5.	Zilly, Buhmann, and Mahapatra (2017)	Ensemble learning based convolutional neural network (CNN)	Accuracy = 94.1 %
6.	Muhammad et al. (2017)	Deep learning method (HDLM)	Accuracy = 93 %
7.	Li, Cheng, Wong, and Liu (2016)	Support vector machines (SVMs) on the deep features	Accuracy = 83 %
8.	Raza et al. (2014)	mRGCPL&SAP method which is a combination of macular retinal ganglion cell plus inner plexiform layer (mRGCPL) and Standard automated perimetry (SAP)	Accuracy = 86 %
9.	Acharya, Dua, Du, and Chua (2011)	Random forest	Accuracy = 91.7 %
10.	Dua, Acharya, Chowriappa, and Sree (2012)	Sequential minimal optimization (SMO)	Accuracy = 93.33 %

4.5 Evaluation results

Both YATSI and LLGC were trained on different image-related features that we extracted using PHOG and Gabor filter. The training dataset consisted of 859 “Non-glaucoma” and 859 “Glaucoma” fundus images collected from social media. Table 2 summarizes the prediction quality that was assessed via tenfold cross-validation technique.

From Table 3, it can be observed that the YATSI classifier using PHOG features was able to achieve 93.25% accuracy, 90% kappa statistic, and 5% RMSE. These results were higher than the prediction results of Gabor filter (82.15% accuracy, 81% kappa statistic, and 12 % RMSE). From Table 3, it can also be noticed that the LLGC algorithm had the highest prediction capability using PHOG-related features with accuracy (77.82%), kappa statistic (76%), and RMSE (19%), compared with the prediction results of Gabor-related features (accuracy 62.86%, kappa statistic 60%, and RMSE 32%). As a result, image features extracted with the PHOG method were found to be extremely useful in enhancing the prediction quality of YATSI and LLGC classifiers. The results also showed the potential of YATSI in detecting glaucoma disease using “Glaucoma” fundus images.

Table 2: Image classification results

Algorithm	Feature extraction approach	Accuracy (%)	Kappa statistic (%)	RMSE (%)
YATSI	PHOG	93.25	90	5
	Gabor	82.15	81	12
LLGC	PHOG	77.82	76	19
	Gabor	62.86	60	32

In the second phase, we evaluated the performance of text classification using image classification by measuring the consistency level between the two types of classifications on newly collected data (validation dataset). The validation data consisted of 2000 social media posts—each post has a piece of text and a digital fundus image.

We performed the text classification process using the YATSI classifier. The emotional features extracted from the texts were used to predict whether a text is either “Non-glaucoma” or “Glaucoma”. For image classification, the YATSI method was implemented using PHOG features of images to predict a label for each fundus image (either “Non-glaucoma” or “Glaucoma”). The kappa statistic results showed 96 % agreement between the two-labeling methods. Based on this, it can be said that the proposed method can offer a reliable way for the detection of Glaucoma.

5. Discussion and Implications

The sentiment analysis results showed the potential of the proposed method in characterizing and predicting the glaucoma disease from Twitter. Precisely, the sentiment analysis results outlined the importance of certain emotions (anger, fear, and sadness) in predicting the glaucoma disease accurately (98.91%). Certain topics were also found to be associated with these emotions as a result of people's sharing of their stories on Twitter. The use of time series was also found to be beneficial in underlying frequent terms used by people with glaucoma. This finding extends the work of Jampel et al. (2007) who reported that glaucoma patients are likely to experience emotional disbalance as a result of being afraid of losing vision in the future. Such finding is also supported by Ciuraru (2016) who explained that fear of blindness, increased anxiety and depression are all can lead glaucoma patients to share negative sentiments about their vision status. In light of that, patients who have fear form being blinds, they have negative emotion that is associated with sadness emotion (Dorison et al., 2020). This explains the existence of such a negative sentimental feature in our tweets. In addition, our findings of the current study are consisted with prior work by Stamatiou et al. (2021) who outlined a direct relationship between glaucoma patients and the negative sentiments.

Our result also showed that several topics were posted and shared among Twitter users in relation to glaucoma. The first topic was about various glaucoma symptoms that patients experienced such as headache, blurred vision, halos, eye redness, and eye pain. These topics were found to be extremely important in the recognition of glaucoma in previous studies. The literature outlined a number of terms and topics that are used across glaucoma patients like head pain, vomiting, and nausea (Rossi, Tinelli, Pasinetti, Milano, & Bianchi, 2009; Shalini & Srinivasan, 2021; Tufail & Saghir, 2021). In addition, the use of multitude method was found to be effective in improving the classification results by eliminating the outliers of some specific topics related to the glaucoma disease (Q. Yu, Miche, Séverin, & Lendasse, 2014). This finding is in line with some previous studies on machine learning such as Ebadati and Tabrizi (2016) who demonstrated high efficiency in utilizing this method with big data through the application of genetic algorithms and k-means clustering.

This proposed procedural approach can advance the current efforts toward developing clinical decision support systems capable of detecting diseases online. The use of topic modeling technique in identifying the key terms associated with glaucoma adds to the current development of online prediction tools which mostly rely on one data source. Being able to accurately identify the spread of glaucoma in the population can open new opportunities for health decision makers to take the necessary steps to limit the spread of this disease. We also believe that using multiple data mining techniques in characterizing previously identified glaucoma topics can be beneficial to system developers.

7. Limitations and Future Works

There are some limitations that this study could overcome in the future. First, this study used tweets in the English language that were published within 6 months period. Second, the number of topics identified in this study was limited to headache, blurred vision, halos, eye redness, and eye pain. Third, the total number of association rules was limited to the number of topics and themes found within the extracted data. Based on these, this study hopes that future research can investigate the applicability of our method in predicting glaucoma using non-English terms. Future studies can also be directed at using other clustering methods to explore the possibility of finding other hidden patterns. Future studies can also consider examining other emotions and explore their potential in detecting glaucoma conditions. Since this study used glaucoma as the case for testing the proposed method, future studies could adopt our technique to diagnose other eye diseases to enrich the overall understanding of the role of disease-related emotions in the disease recognition process on social media platforms.

8. Conclusion

This study proposes a novel approach for early-stage glaucoma recognition using Twitter messages. Therefore, glaucoma tweets were collected via Twitter free streaming API. The data were prepared via several preparation tools. Themes related to glaucoma were extracted using LDA. Then, association rules mining was used to extract the disease-related symptoms from each theme. Our results showed that certain emotions, such as fear and sadness emotions, were highly associated with glaucoma statements. The results exhibited that certain emotions, such as fear and sadness emotions, were highly associated with glaucoma statements. In addition, observations from this research evidently showed that emotion-related features have a significant impact on improving the prediction process of the applied machine learning algorithms. As a result, this study proposed a low-cost procedural mechanism for the early-stage detection of eye disorders using microblogs data. The proposed method improves the decision-making process via users' sentiment embedded in the data.

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