Gaze-based Interest Detection on Newspaper Articles

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ABSTRACT

Eye tracking measures have been used to recognize cognitive states involving mental workload, comprehension, and self-confidence in the task of reading. In this paper, we present how these measures can be used to detect the interest of a reader. From the reading behavior of 13 university students on 18 newspaper articles, we have extracted features related to fixations, saccades, blinks and pupil diameters to detect which documents each participant finds interesting or uninteresting. We have classified their level of interests into four classes with an accuracy of 44% using eye movements, and it has increased to 62% if a survey about subjective comprehension is included. This research can be incorporated in the real-time prediction of a user's interest while reading, for the betterment of future designs of human-document interaction.

CCS CONCEPTS

• **Computing methodologies → Activity recognition and understanding**;

KEYWORDS

Eye tracking, reading, interest, fixation, saccade, blink, pupil diameter, human-document interaction

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1 INTRODUCTION

Reading has always been the foundation of all learning and thereby education. This soft skill is a source of creative power but one which is to be easily instilled in people. While reading, eyes perceive the content immediately and they form a vocabulary of their own comprised of fixations, saccades, regressions, pupil diameter and blinks [Yang and McConkie 2001]. These measures behave differently in changing circumstances and give us an insight of cognitive states – thought processes and emotions – during the reading task [Rayner et al. 2006]. Various studies have been done on using these metrics to analyze a person's attention, tiredness and cognitive load. In this paper, we pursue to study a reader's interest and its association to eye-tracking metric behaviors.

Interest in reading can be motivated by concentration, curiosity, and demand. It may not rise out of habit but it will help motivate the habit and subsequently the learning process. Interest motivates earnestness in a person. According to Ibrahim Bafadal, "Reading is a process of capturing or acquiring the concepts intended by the author, interpret, evaluate the author's concepts, and reflect, or act as intended of those concepts". Hence it not only depends on the ability to interpret and evaluate the contents but also the will to do the same for comprehensive understanding [Hidi 2001; Raney et al. 2014; Squires 2014].

This urge in reading, if recognized, can be used to improve the data made available to the reader and also help in better human-document interaction and the design. Predicting a reader's interest can help to make document more interactive or dynamic [Biedert et al. 2010]. Research done on dynamically changing text shows that reading dynamic text is much smoother and faster than reading static text [Uetsuki et al. 2017]. Eye gaze, if used to predict a user's interest, comprehension and difficulty, can influence his/her interaction with the learning environment and thereby affect the learning process [Copeland et al. 2014]. This can further assist teaching techniques and promote understanding and active interest in students.

On the basis of the motivation mentioned above, we propose an interest detection method by utilizing an eye tracker. Research questions addressed in this study are two-fold. RQ1: How accurately can eye movements estimate a reader's interest? RQ2: Since reading behaviors are different for each reader, which measurement can be used as a common feature?

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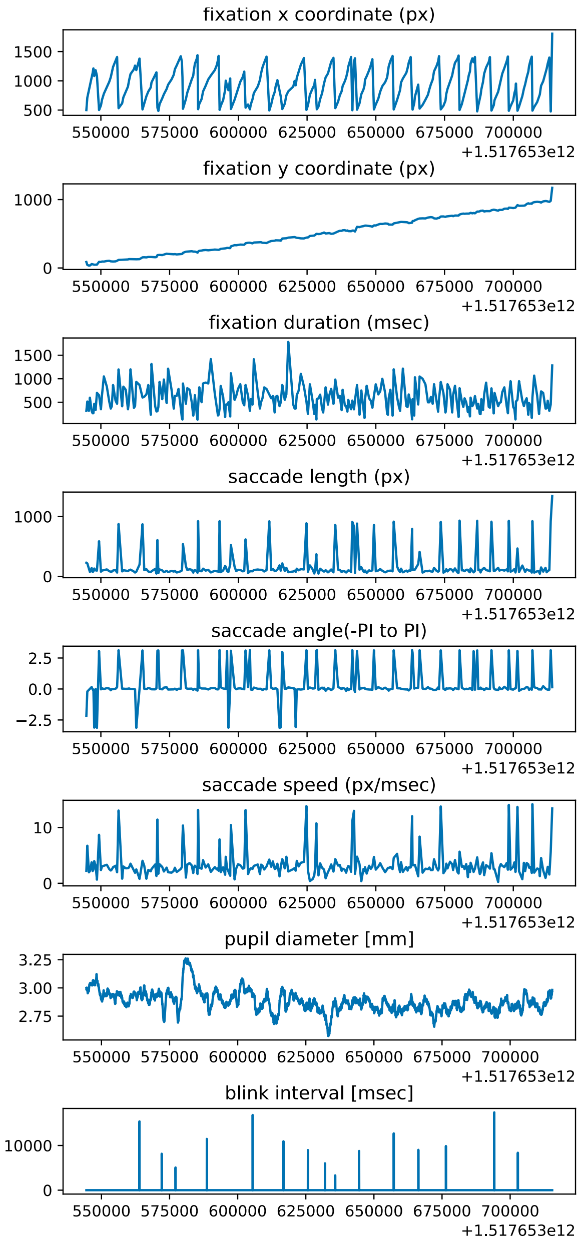

Figure 1: Gaze events calculated by a signal of an eye tracker

2 PROPOSED METHOD

2.1 Gaze event detection

Figure 1 shows an example of the gaze events while reading an article. Eye movements while reading are composed of three basic metrics: fixations, saccades and blinks. A fixation occurs when the gaze falls on something of interest to the screen area and usually lasts for about 100 - 150 ms. The rapid movement of the eye between fixations is called a saccade. A blink is a semi-autonomic rapid closing of the eyelid. Pupil diameters can be also obtained from an eye tracker. We detect the gaze events by following steps.

Figure 2: An example of a news article and eye gaze (circle: fixation, line: saccade) on a document

As preprocessing, we filter raw eye movements to get fixations and saccades on the basis of the approach proposed by Buscher et al. [Buscher et al. 2008]. The midpoint of the left and the right gaze coordinates is taken as the gaze point, only if both values are non-zero, else the (left or right) non-zero coordinates is taken as the gaze point. A fixation typically consists of more than six successive gaze locations grouped in succession. This makes the minimum fixation duration 100ms as mentioned earlier for data recorded at a rate of 60Hz. The successive gaze points making a new fixation should fit inside a threshold rectangle of 30x30 pixels. All further gaze points falling inside a 50x50 pixel rectangle is considered to belong to the current fixation. This is done so that noise and small eye movements are tolerated. If the gaze point does not fall in the rectangle, it is either an outlier or the start of a new fixation, which further merges with six other points. The fixation is considered to have ended if at least six successive gaze points cannot be merged.

The movement or transition from one fixation to the other is recorded as a saccade. Saccades are further divided into forward saccades and backward saccades. The x-coordinate of successive fixations denotes the direction of the saccade. Forward saccades imply regular reading behavior, while backward saccades can either be regressions or line breaks. Regressions are backward eye movements which allow re-reading of the text [Booth and Weger 2013]. Line breaks are separated from regressions by analyzing the length of the backward saccade. If the length is equal to or greater than the length of a line, then they are categorized as line breaks (observed as peaks in the saccade length in Figure 1).

Further, we use pupil diameter obtained from raw gaze data, which is the average of left and right pupil diameter, if both are non-zero. Another characteristic eye behavior we record is blink. The average duration for a blink of a human eye is 100-400ms. Hence, 6-24 consecutive zeroes in the left and the right gaze coordinates are considered as one blink in our approach. The average latency of two consecutive blinks is one second and blinks detected in between are considered as noise.

Table 1: List of features

No.	feature
1-2	{mean, standard deviation} of fixation duration
3-4	{mean, standard deviation} of forward saccade length
5-6	{mean, standard deviation} of forward saccade speed
7-8	{mean, standard deviation} of regression length
9-10	{mean, standard deviation} of regression speed
11-12	count of {forward saccades, regressions}
13	regression ratio
14-15	{mean, standard deviation} of pupil diameter
16	blink frequency
17	standard deviation of blink interval

2.2 Feature calculation

On the basis of the gaze events, we extracted seventeen features for further analysis, as listed in Table 1. *Fixation duration* is the time taken for each fixation. *Forward saccade length* is the distance between the two consecutive fixations that make the saccade. *Forward saccade speed* or *Regression speed* is the length of the saccade divided by the time taken for the saccade. *Regression ratio* describes the fraction of regressions out of the total number of saccades (i.e., (No.11 / (No.11 + No. 12)). *Regression length* is the distance between the two fixation coordinates that makes the regression. *Pupil diameter* is the diameter of the right pupil obtained from the raw gaze data, provided the x and y gaze coordinates are non-zero else taken as zero. Since pupil diameter is user and environment dependent, it was taken as a relative value compared to the pupil diameter during the questionnaire which was taken as a baseline. *Blink frequency* is the number of blinks divided by the total time taken by the reader (for each document). *Blink interval* is the time lag between two consecutive blinks.

2.3 Classification

The aforementioned features were used for classification of the eye tracking data into four levels of interest. We utilize either of *Support Vector Machine* (SVM) or *Random Forest Classifier*. SVM categorizes the test data with a separating optimal hyper plane which is defined by the labeled training data. Random Forest Classifier randomly selects subsets of training data and creates sets of decision trees and further uses the votes from the decision trees to find the test data category. Selecting hyper parameters (C, kernel and gamma in SVM and the number of estimators, the maximum depth of the tree, the maximum features to consider, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node in Random Forest) is crucial and non-trivial. In our approach, we used 3-fold grid search cross-validation as a hyper parameter optimization technique. It searches exhaustively through a manually defined set of parameters and finds those that achieved the highest score in the validation procedure. We separate training data into training for parameter optimization and the evaluation for each classification.

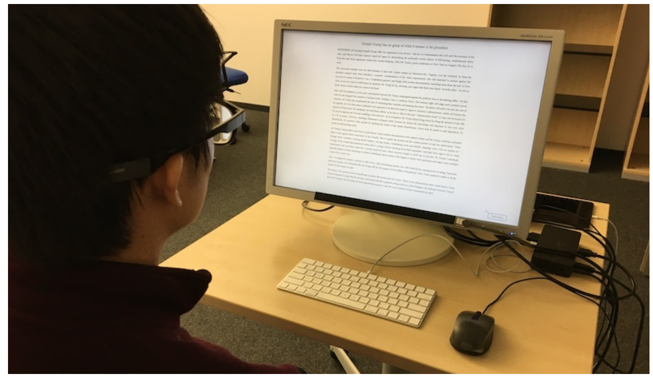

Figure 3: An overview of the experimental setup. A participant is reading a news article on a display with SMI REDn Scientific 60Hz remote eye tracker.

3 EXPERIMENT

In order to evaluate our proposed interest detection method, we conducted an eye tracking experiment. The following section describes the experimental design and the analysis results.

3.1 Experimental design

Figure 3 shows an overview of the experimental setup. We used an SMI REDn Scientific 60Hz remote eye tracker set up alongside a normal computer desktop to record gaze data.

Newspaper articles seemed to capture the purpose of the experiment better than any other text. To capture the reader's interest, we obtained a wide range of topics from different platforms like technology, politics, sports, cooking etc. Thirteen university students (mean age: 25, std: 3, male: 6, female: 7, 2 of them are familiar with eye tracking) participated in the experiment where each of them was asked to read eighteen newspaper articles comprising of 403 - 649 words each (mean: 555, std: 70) as shown in Figure 2.

After reading each document, participants answered three questions. (1) the level of interest they had in the article, which was used as ground truth (from 1 to 4, where 1 indicated "No interest" and 4 indicated "High interest"), (2) a self-assessment about how much of the content the reader understood (subjective comprehension, from 1 to 4, where 1 indicated "I couldn't understand the article" and 4 indicated "I could understand the article"), and (3) one question about of the article (i.e., objective comprehension).

The recordings were done in two sessions of one hour each, in order to avoid eye-fatigue and these were conducted in a controlled environment. The tracker and the desktop were maintained in a stable position. The lighting of the room was set so as not to affect the gaze data (pupil diameter). Calibration was done after reading every document to avoid error or shift of the gaze points.

We followed three different approaches to separate the train-test data before classification. *Leave-one-recording-out* uses each recording (data of each participant on each document) as test data, the rest as training and the average of the accuracy in all cases together is taken as the classification accuracy. Similar to this approach, *leave-one-document-out* approach exempts the data of a document completely from the training set and uses it for testing.

Table 2: Classification accuracies using SVM [%]

	leave-one -part.-out	leave-one -doc.-out	leave-one -rec.-out
1. reading speed	31	30	30
2. subjective comprehension	**59**	**60**	58
3. objective comprehension	34	35	33
4. eye movements	28	44	44
combination 1 and 4	26	43	44
combination 2 and 4	40	59	**59**
combination 3 and 4	28	44	43
combination all	41	58	57

Table 3: Classification accuracies using Random Forest [%]

	leave-one -part.-out	leave-one -doc.-out	leave-one -rec.-out
1. reading speed	25	29	28
2. subjective comprehension	**55**	55	52
3. objective comprehension	30	31	34
4. eye movements	30	46	42
combination 1 and 4	35	43	41
combination 2 and 4	44	**61**	**62**
combination 3 and 4	30	41	39
combination all	46	**61**	58

Leave-one-participant-out approach uses one the data from all participants except one as training and uses the data from the left-out participant as testing. It is quite significant as, in a realistic scenario; the system does not have training data from a new user.

3.2 Results

Table 2 represents the classification accuracies using SVM. The most frequently selected hyper parameters are C: 32, gamma: 0.125, kernel: Radial Basis Function. Table 3 shows the classification accuracies using Random Forest. The most frequently selected hyper parameters are the number of estimators: 100, the maximum depth of the tree: 10, the maximum features to consider: square of the number of all features, the minimum number of samples required to split an internal node: 10, the minimum number of samples required to be at a leaf node: 3. We also incorporated feature reduction techniques like PCA and LDA, but found no commendable improvement in the classification.

The distribution of the predicted classes are observed as confusion matrixes shown in Figure 4 and Figure 5. The overall correlation between the various features used and the labels are still quite small. However, when individual participants were considered, from correlations between features and interests shown in Figure 6, we found that there was (1) a negative correlation between mean/standard deviations of fixation duration with the interest labels, (2) a considerably small positive correlation existed for the standard deviation of regression speed, (3) also with the number of forward saccades. But this was observed for only half the number of participants or less, the rest having no or very slight

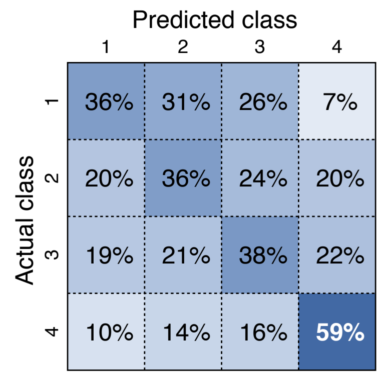

Figure 4: A confusion matrix of the SVM classifier with leave-one-recording-out training using only gaze features. Mean accuracy: 44%.

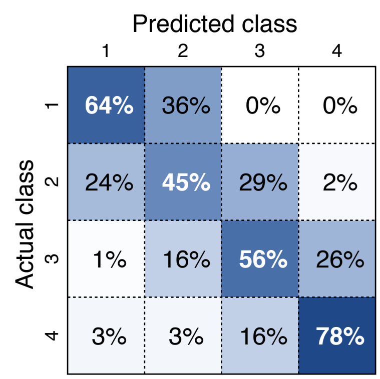

Figure 5: A confusion matrix of the Random Forest classifier with leave-one-recording-out training using subjective comprehension and gaze features. Mean accuracy: 62%.

correlations with the features. Feature importances were also computed using the Random Forest classifier as seen in the Table 4. Mean forward-saccade speed, mean fixation duration and mean regression speed was found to have the highest importance (in that order) and number of regressions had the lowest.

We included non-eye related measures like reading speed and the level of subjective/objective comprehension of the user. The accuracies using SVM and Random Forest classifiers are tabulated in Table 2 and Table 3. Figure 6 shows the Pearson's correlation of the features for each participant with the level of interest. The level of subjective comprehension of a person can be seen to have a very high effect on a person's level of reading interest (denoted by red-high and blue-low). We got an accuracy of 60% when subjective comprehension was used for classification (Table 2). And, an accuracy of 61% for leave-one-document-out when all measures - reading speed, subjective and objective comprehension, eye gaze features, were used (Table 3). By using subjective comprehension and eye-related features, we achieve an accuracy of 62%.

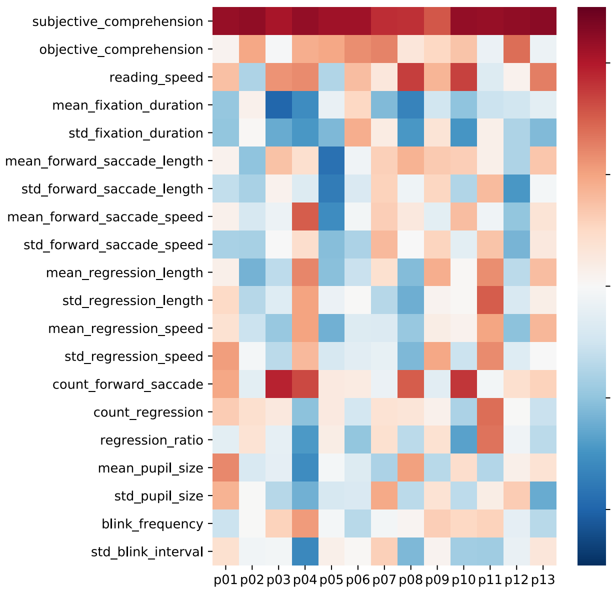

Figure 6: Pearson correlations between features and interests of each participant

Table 4: Importance of features in the Random Forest

feature	importance
subjective comprehension	0.2760
mean of forward saccade speed	0.1019
mean of fixation duration	0.0961
mean of regression speed	0.0524
count of forward saccade	0.0471
regression ratio	0.0413
standard deviation of fixation duration	0.0408
standard deviation of regression speed	0.0386
standard deviation of blink interval	0.0368
standard deviation of forward saccade length	0.0365
objective comprehension	0.0337
reading speed	0.0336
mean of regression length	0.0305
mean of forward saccade length	0.0213
blink frequency	0.0213
standard deviation of regression length	0.0205
standard deviation of forward saccade speed	0.0201
mean of pupil diameter	0.0191
count of regression	0.0163
standard deviation of pupil diameter	0.0161

3.3 Discussion

Although the accuracies were not as high as expected, this research threw light on using a remote eye tracker for cognitive state measurement. We found that mean forward-saccade speed, mean fixation duration and mean regression speed plays a vital role in predicting a reader's interest. And that SVM with an RBF kernel is best to classify gaze-based features.

However, a higher correlation of the features to the labels was expected, though it was observed to be quite small. The correlation was quite different in the case of each participant for all features except for ones earlier mentioned. This led us to believe that cognitive predictions are user-dependent and not just document-dependent. For example, pupil diameter may not undergo the same changes in every user during the same psychological process. These features are dependent on the user and his/her cognitive state. We also found that the collection of ground truth related to interest and understanding are widely prone to human error and individual behavior.

Subjective comprehension of a person has a very high correlation to the level of interest while reading, which makes sense, since interest can only be realized if the person truly understands the text. But using eye measures while reading is an added advantage to understand this and should be deeply explored, since it can be realistically collected while reading without reader intervention.

4 RELATED WORK

There has been a lot of study on designing systems which focus on visualization and interaction methods that allows the user to better attend to a task with minimal mental effort. Our research focuses on interpreting how interested the person is in reading or doing the task at hand. This in turn can be used to provide more information or better information that the user subconsciously requires.

4.1 Brain sensors

Brain activity or cognitive processes can be measured through EEG and MEG, by capturing changes in magnetic fields at the scalp caused by electrical currents in brain neurons [Frey et al. 2016]. It refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp [Lan et al. 2005]. fMRI or Functional magnetic resonance imaging, measures the changes in blood flow to an area of the brain to detect which part of the brain is in use. Functional Near-Infrared Spectroscopy (fNIRS) uses near-infrared spectroscopy for functional neuroimaging and measures brain activity through hemodynamic responses [Ishimaru et al. 2014]. However, using these techniques in day to day activities are quite intrusive. They can neither be used in situ nor in public due to the time consuming and expensive setup and the complex analysis.

4.2 Physiological sensors

There has been a growing interest in the study of the relation between cognitive performance and heart rate variability (HRV). HRV is a simple measurement of interactions between the autonomic nervous system (ANS) and the cardiovascular system. The analysis of the HRV is based on the study of temporal oscillations between heartbeats [Luque-Casado et al. 2013]. Electrodermal activity (EDA; changes in electrical conductance of the skin) is a sensitive psychophysiological index of changes in autonomic sympathetic arousal that are integrated with emotional and cognitive states [Brishtel et al. 2018]. HRV, EDA, respiration and brain signals have been used to predict mental stress and cognitive load in various studies [Critchley 2002; Masood 2015]. The activity of ANS can be also measured by the nose temperature. If autonomic nervous system is active than parasympathetic nervous system (i.e., a person feeds high workload), blood vessels constrict and therefore the nose temperature drops. It can be measured by an infrared thermal camera [Ishimaru et al. 2017] Abdelrahman et al. have recorded nose and forehead temperatures under different task difficulties and found significant changes [Abdelrahman et al. 2017].

4.3 Eye tracking and gaze oriented features

Various researches discuss eye tracking measures and its hand in interpreting cognitive processes and cognitive load. The measures used are voluntary – fixations and saccades, and involuntary – pupil diameter and blinking. According to Ruddmann et al., the direction of gaze indicates repeated interest in an area and the importance of the area of interest in the current activity [Rudmann et al. 2003]. Chen et al. have observed that fixation duration and fixation rate are indicators of an increase in attention on the current task [Chen et al. 2011]. They delved into the relevance of saccades in interpreting human mental effort in solving a task. They have also found that an increase in blink interval and a decrease in blink rate indicated high mental effort and that studying the diameter of the pupil helps to realize the task difficulty and the cognitive effort. Blinking is more often an involuntary measure but in certain cases it is a voluntary measure which can be studied to measure attention and tiredness [Zagermann et al. 2016]. Saccade speed and length with other measures achieved high accuracy in measuring human performance. On the other hand, Manuel et al. suggested a decrease in saccade speed indicated tiredness and an increase in the same indicated task complexity [Barrios et al. 2004]. According to them, an increase in blink rate, a decrease in blinking speed and a decrease in the eyelid openness are indicators of tiredness and stress. Ishimaru et al. have investigated reading behaviors of students on a textbook in Physics [Ishimaru et al. 2018]. They have proposed two types of expertise prediction method: utilizing fixation durations on Areas of Interest and utilizing mean and standard deviation of fixations and saccades in a subsequence. Porta et al. have further observed that decrease in pupil diameter at the end of the task indicated tiredness [Porta et al. 2012]. Gaze has been used in adaptive scrolling algorithms to allow continuous reading of newspaper articles in large public displays [Lander et al. 2015]. In this study, Lander et al. uses head mounted eye trackers in a multi-user scenario to study the effect of this approach on the user's reading speed.

4.4 Position of our study

These papers give us a deep understanding of how eye movements can be used to measure various cognitive factors like human mental effort, attention, cognitive load, tiredness etc. Our goal is for the system to measure the degree of interest the reader has on the content, so that more data can be made available to the user and to improve human-document interaction. Kunze et al. have explored how to detect reader engagement from eye metrics and nose temperature with a dataset obtained from 5 users and achieved 100% accuracy for binary classification [Kunze et al. 2015]. The features used were blink frequency, nose temperature, number and duration of fixations, number and angle of saccades. We have sought to improve this with a larger dataset of 13 users, each reading 18 documents. We further used features obtained from pupil diameter and regressions for a four-class classification.

5 CONCLUSION AND FUTURE WORK

This research demonstrated that eye measures from a remote eye tracker can be successfully used to predict a reader's interest. We obtained data from experiments conducted with 13 students, who read 18 newspaper articles each. We extracted seventeen features from raw gaze data obtained from the tracker and used it for further classification of the data into different levels of interest. Although the correlation of the features with the interest labels were not as high as expected, forward-saccade speed, fixation duration and regression speed were significant.

This work can be extended to include data from other sensors like an infrared thermal camera to measure nose temperature and a physiological wristband to measure heart rate and skin electrical conductance. Data acquisition could also be improved by controlling the environment to present a stress-free or at-home experience for the reader. Also, unsupervised learning could be used for data classification to avoid human error in the ground truth.

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