Abstract: Instagram is one of the most popular social networks for marketing. Predicting the popularity of a post on Instagram is important to determine the influence of a user for marketing purposes. There were studies on popularity prediction on Instagram using various features and datasets. However, they haven't fully addressed the challenge of data variability of the global dataset, where they either used local datasets or discretized output. This research compared several regression techniques to predict the Engagement Rate (ER) of posts using a global dataset. The prediction model, coupled with the results of the popularity trend analysis, will have more utility for a larger audience compared to existing studies. The features were extracted from hashtags, image analysis, and user history. It was found that image quality, posting time, and type of image highly impact ER. The prediction accuracy reached up to 73.1% using the Support Vector Regression (SVR), which is higher than previous studies on a global dataset. User history features were useful in the prediction since the data showed a high variability of ER if compared to a local dataset. The added manual image assessment values were also among the top predictors.

Keywords: Social media, Instagram, popularity trend, machine learning, prediction model.

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1. Introduction

Instagram is the fastest growing social network, with nearly 5% growth each quarter [19]. With 1m active users as of June [20], it becomes the best platform for brand marketing for a millennial audience [10] and the platform with the highest Engagement Rate (ER) [8]. The number of likes is commonly perceived as a social status [5], which is useful for marketing purposes. However, it can create a stressful experience for users [16].

Predicting popularity on Instagram is important to find the best possible influencer for brand marketing [15], and to help the general public to discover trends on Instagram. There were studies on Instagram’s popularity prediction, with features such as image content [14, 27], hashtag [4], image aesthetic [17], time [6], and metadata. However, there were no existing studies that addressed the challenge of data variability in global dataset. Existing studies have either small data variance due to usage of local-specific dataset [28], or small variance of output due to discretized output [27].

This research used hashtag analysis, image content, image quality, user history, as well as metadata as the features for prediction. Several social studies have shown that hashtags [12, 18] and image content [4] have a vital contribution to popularity. The output of the prediction is the ER of a media within one month from the upload date. The ER is the number of likes divided by followers. Usually, there is a peak period for likes, where a post will get far fewer likes after a month [1]. Thus, this research predicted the post popularity during the peak period.

The following questions were addressed in this research, i.e., (R1) what is the relation between the features (hashtag, image analysis, user history, metadata) and the Engagement Grade (EG)? (R2) How do these features affect the prediction of ER? (R3) What is the best regression method for popularity prediction?

The following hypothesis was formulated in this research, i.e., (H1) Global dataset has more ER variability.

This research aims to analyze the ER and the factors that affect it, as well as create a machine learning regression model to predict them. The contributions of this research are as follows:

- This is the first study that analyzes popularity on Instagram using global dataset.
- Compared to previous studies, we added hashtags analysis, image assessment, and user history features to predict the popularity of a post.

The result of this study is beneficial for both business and regular users. The extensive features set used in this study helps the general public to understand the complexity of post popularity on Instagram. The paper is organized as follows: related works, methodology...
(data collection and features extraction), popularity analysis, and popularity prediction.

2. Related Works

There were studies on popularity on Instagram, with some more focused on the statistics, some on predictions. Most of the studies used metadata (number of followers, posts, etc.) as a feature. There were additional features such as image content/category, image quality, text/sentiment analysis. There were four types of popularity metrics in the recent studies, i.e., likes [4, 6, 9, 14], engagement level [17], intrinsic image popularity [7], growth of likes [1], and categorized output, such as popular-unpopular [27].

There were two types of image analysis in the prediction of popularity in recent studies, i.e., content analysis and quality analysis. Image content analysis can be either categorization or featureization. Image category is a single field, such as brand image, people, selfie, etc., [14], whereas image feature is a field with multiple aspects, such as selfie, outdoor, food, girls, etc., [4]. Image aesthetic analysis was also used for popularity prediction [17]. In this study, we added manual image assessment values for popularity prediction, which hasn't been used in previous studies.

All existing studies that used hashtags were either a statistical study on the effect of hashtags in increasing popularity [4, 6] or using hashtag count for prediction [9, 17]. Existing popularity prediction studies only used hashtag counts for prediction, even though a recent study has found the usefulness of hashtag in terms of increasing likes [3]. Thus, we further exploit hashtag by extracting hashtag popularity and visibility values.

In terms of the dataset, some studies used local or region-specific datasets or global datasets. Iranian Instagram business accounts (consisted of 3 users and 281 posts) were used in a study [28], with prediction accuracy of up to 90.77% for three output labels. Single lifestyle magazine data was used in a study [6], with prediction accuracy of up to 88%. The global dataset is more challenging and expected to produce lower prediction accuracy, only up to 71.19%, utilizing two output labels (popular, unpopular) [27].

Overall, existing studies lacked prediction on Instagram posts' popularity using the global dataset. While there was a study using a global dataset [27], it was focused on how to raise the popularity of a specific user. Thus, we used the dataset collected from global hashtags for popularity analysis and prediction.

There were other studies on various social media platforms, such as Flickr [9], Twitter [2], YouTube, and Facebook [23], which are different from Instagram in terms of features and ER.

3. Research Methodology

There were four phases in this research, i.e., data collection, data filtration, analysis, and popularity prediction, as shown in Figure 1.

3.1. Data Collection

Data collection was started by collecting 2,000 top hashtags from Top-Hashtags [22]. From the hashtags list, posts were collected using the Instagram Application Programming Interface (API). Data collection was done in two periods. The first period was used to get the posts listed under a hashtag at that time. Video posts and posts older than 30 days were removed.

The second period of data collection was used to collect the data of those posts exactly after 30 days of the upload date. Thus, a scraper application was built to constantly check the lifetime of each post available from period 1, and then it re-scraped the data of a post once it reached 30 days since the posting date. There were 6% of posts that were not available in the second period, due to these posts being taken out by Instagram or taken out by the owner.

3.2. Data Filtration

The number of posts data with age less than 30 days was 102,698 posts. From a hashtag, there are posts that were not available in the first period of data collection due to period 1, and then it was removed. The number of posts data with age more than 30 days was 6% due to the removal of some posts that were not available in the second period. The number of posts data with age less than 30 days was 102,698 posts. From a hashtag, there are posts that were not available in the first period of data collection due to period 1, and then it was removed.
criteria were removed, i.e., (1) Posts from users with < 100 followers, (2) Posts from users with total posts < 10, and (3) Posts with the number of likes < 5, and (4) Posts from users with > 1 million followers. Finally, the next step is to balance the posts, to get 50% posts from top posts and 50% from most recent. The final number of posts was 19,324 (from 16,804 unique users), which was used throughout this research.

4. Features Extraction

The source of the features was from the following table, i.e., user, post, hashtag. Other sources are from NIMA, annotation, and users' history. The list of features group and the features is as follows:

- **User Features (U)**
  - flg: Number of following (from 0 to 7,500).
  - flr: Number of followers (from 100 to 1,000,000).
  - pos: Number of posts (from 21 to 49,957).
  - flgc: Number of following category, i.e., 0 (for 0-500), … 9 (for 4,501-5,000), 10 (for > 5,000).
  - flrc: Number of followers category (0 to 10), according to Figure 5.
  - posc: Number of posts category, i.e., 0 (for 0-500), 1 (for 501-1,000), … 10 (for > 5,000).
  - bl: Biography length (characters).
  - lin: Link availability, i.e., 0 (no) or 1 (yes).

- **Post Features (P)**
  - hc: Hashtags count.
  - it: Location tag, i.e., 0 (no location), 1 (using location).
  - cl: Caption length (characters)
  - day: Upload day, i.e., d1 (Sunday) to d7 (Saturday).
  - tf: Upload time, i.e., t1 (00.00-03.00) to t8 (21.00-24.00).
  - ut: Number of user tags.
  - pic_*: Nine image content features from section 4.1.

- **Hashtag Features (H)**
  - hp: Hashtags popularity, i.e., sum of (global usage of each hashtag) in the caption.
  - hv: Hashtags visibility, i.e., sum of (growth rate of each hashtag). The growth rate is hours/post.
  - hr: Hashtag reachability, i.e., sum of (global usage * growth rate). This is a combination of hp and hv.

- **Image Assessment (Auto) Features (Aa)**
  - aest: Image aesthetic, i.e., 0.00 (bad)-1.00 (good).
  - tech: Technical quality, i.e., 0.00 (bad)-1.00 (good).
  - Image Assessment (Manual) features (Am)
    - beauty: Beautiful/性感 woman, handsome man, beautiful scenery/object.
    - artistic: Artistic value (if drawing), photographic quality, or arrangements.
    - emotion: Emotional feeling of a human face or objects.
    - unique: Unique objects, or rarely seen image.

- **User History Features (UH)**
  - ef: Engaging followers, i.e., percentage of followers (unique users) who have liked any posts from a user.
  - eo: Engaging outsiders, i.e., same with ef, but for outsiders. Outsider is anyone outside the followers.
  - av_erl: Average of (number of likes/followers)
  - av_erc: Average of (number of comments/followers).
  - st_erc: Standard deviation of (likes/followers)
  - st_erl: Standard deviation of (comments/followers).
  - min_er: Minimum of (likes+comments)/followers.
  - max_er: Maximum of (likes+comments)/followers.
  - av_er: Average of (likes+comments)/followers.
  - st_er: Std. deviation of (likes+comments)/followers.

4.1. Post Features: Image Content

Image content is extracted from the keywords using the accessibility-caption variable. Then, the keywords were grouped into categories based on manual observation. These categories became image content features. If any of the keywords from a respective category match, the feature will be set to 1. Note that we have tried grouping the keywords using several keywords grouping API, but the results were either too many groups or most of the words grouped into “other”.

For example, if the accessibility-caption is “Image may contain: one or more people, people sitting, screen and indoor,” the features pic-activity, pic-wearable, pic-room will be set to 1. The image content features and the respective keywords are:

- **pic_text**: meme, text, that says.
- **pic_nature**: beach, sky, mountain, cloud, night, ocean, beach, snow, twilight, bridge, christmas, fireworks, outdoor, flower, plant, tree, grass, candle, cat, dog, horse, bird, nature, water.
- **pic_vehicle**: car, bicycle, motorcycle, boat, airplane, bus, road, flight.
- **pic_food**: eating, drink, fruit, food, dessert, icecream, sushi, pizza, smoking, coffee.
4.2. Hashtag Features

The hashtag’s popularity ($hp$) of a post is the sum of all hashtags used, as can be seen in Figure 2. The hashtag’s visibility ($hv$ feature) is based on the hashtag’s growth rate ($hg$). The $hg$ value of a hashtag is the average interval (in hours) between every two posts in the most recent posts in the hashtag. This $hg$ value measures how quickly a post gets buried in the most recent list. The $hv$ value of a post is the total of $hg$ value of all hashtags contained in a post caption, as illustrated in Figure 3. This total value (instead of average) gives a perspective of how long a post will appear in the most recent list, contributed by all hashtags in a post.

Choosing hashtags for a post can be tricky since popular hashtags are usually fast-growing. While $hp$ value simulates “audience size,” the $hv$ value simulates “advertisement duration.” High $hv$ value indicates a slow-growing hashtag, which is good for a post since the visible duration is longer. Another feature, the $hr$ (hashtag reachability), is the $hp$ multiplied by $hv$, which is the chance of a post to reach a broader audience.

4.3. Image Assessment Features

There were two image assessment features in this research, i.e., automated assessment and manual (with annotation). The automated assessment was divided into image aesthetic ($ia$ feature) and image technical quality ($it$ feature), which was assessed using the source code available in GitHub [13]. The source code was the implementation of Google's Neural Image Assessment (NIMA) [21]. The technical quality assesses details such as noise, blur, artifacts, and so on, whereas the aesthetic assesses semantic characteristics.

It was suggested that an image’s beauty, artistic, emotion, and unique values highly rely on high-level semantic [11, 25]. This creates many challenges for automatic assessment [11]. Thus, a manual assessment was added. To reduce subjectivity, three human judges (photography experts) were assigned. Each image has to be given a discrete score (from 0 to 3) of beauty, artistic, emotion, and unique values. The values from all judges were averaged and converted to a range of 0.00 to 1.00.

4.4. User History Features

For each user, who is the owner of each post, 15 latest posts (with the age of at least 30 days) were captured. To make a fair prediction, the posts that were available inside the main dataset were excluded from the user history. This is to ensure that the created prediction model would be able to forecast future posts of a user.

Besides the post data itself, the likers and the followers of each user were captured. By using these data, the unique likers can be captured. A unique liker is either a follower, which is called as engaging followers ($ef$); or a non-follower, which is called as engaging outsiders ($eo$). Both $ef$ and $eo$ were used to estimate the active audience size of each user in order to improve prediction accuracy.

4.5. Prediction Output

The output of the prediction is the ER within one month from the upload date, which is the number of (likes+comments) divided by followers. The range of the ER was 1.1% to 19.9%.

5. Popularity Analysis

In this section, features are plotted to examine the contribution of each factor to the ER. In Instagram market studies, it was proven that the number of followers highly contributes to the ER. For example,
users with <2,000 followers have an average ER of 10.7%, all the way up to users with >1 million followers have 1.5% average ER [24]. The linear trend line in Figure 4 shows that the ER is decreasing by 0.026% for every 10,000 followers increase, according to our data.

Figure 4. Number of followers vs. ER.

The ER comparison is not fair across users with a different number of followers, since higher tier ER values are produced from users with lesser followers. This is consistent with a report [24]. Thus, for a fairer comparison, the EG metric was defined. The ER chart [24] was divided equally into 12 regions, with 4 below average regions and 8 above average regions, as can be seen in Figure 5.

Figure 5. Follower category (flr) and EG regions.

EG is ranging from 1 to 12. For example, for a user with 260K followers, and ER 3.0%, the EG is 5 since it is inside region 5. The EG metric sets a higher standard for users with lesser followers, and vice versa.

5.1. Contribution of Users Features on EG

The following Table 1 shows the EG and user metadata features comparison. The table shows that the number of followers and following are equally distributed, which shows a fairer comparison, unlike Figure 4. The features bl and lin didn’t show a significant contribution to EG. Interestingly, the fflg and pos decrease as the EG increase, as seen in Figure 6. This means that better EGs were coming from less spammy users, as also suggested by [17].

| EG | Data Count | fflg | fflr | pos | bl | lin |
|----|------------|------|------|-----|----|-----|
| 1  | 675        | 1361 | 1412 | 2297.8 | 136.3 | 0.60 |
| 2  | 2,120      | 1137.7 | 3083.3 | 1600.8 | 135.2 | 0.56 |
| 3  | 2,786      | 1099.7 | 94837.7 | 1952.1 | 142.9 | 0.56 |
| 4  | 2,358      | 1021.2 | 86672.5 | 1746.5 | 146.1 | 0.58 |
| 5  | 2,146      | 1007.1 | 80331.6 | 1535.5 | 144.3 | 0.58 |
| 6  | 1,745      | 1005.4 | 72425.7 | 1365.8 | 143.5 | 0.54 |
| 7  | 1,495      | 1174.3 | 74240.5 | 1267.8 | 152.0 | 0.58 |
| 8  | 1,101      | 1094.2 | 69767.0 | 1312.9 | 150.9 | 0.61 |
| 9  | 994        | 1133.0 | 67713.8 | 1206.8 | 150.0 | 0.58 |
| 10 | 802        | 1120.1 | 67714.2 | 1015.5 | 143.5 | 0.56 |
| 11 | 662        | 1102.9 | 61316.8 | 898.9 | 148.6 | 0.55 |
| 12 | 2,440      | 881.6 | 69483.7 | 740.7 | 139.5 | 0.53 |

5.2. Contribution of Post and Hashtag Features on EG

The next comparison is EG with post features, shown in Table 2. One important aspect from this table is that posts with higher EG used more user tags, with an average of 2 user tags on the highest EG. The features hc, cl, lt, didn’t show a significant contribution to EG.

Table 2. EG and post features comparison.

| EG | hc | lt | cl | ut | hp | hv | hr |
|----|----|----|----|----|----|----|----|
| 1  | 17.29 | 0.40 | 328.6 | 0.32 | 0.20 | 0.16 | 0.08 |
| 2  | 17.52 | 0.45 | 347.5 | 0.63 | 0.20 | 0.18 | 0.09 |
| 3  | 15.57 | 0.44 | 367.2 | 0.83 | 0.17 | 0.14 | 0.07 |
| 4  | 15.24 | 0.45 | 353.0 | 0.88 | 0.17 | 0.14 | 0.08 |
| 5  | 15.17 | 0.48 | 376.7 | 1.22 | 0.15 | 0.15 | 0.07 |
| 6  | 15.16 | 0.49 | 375.0 | 1.45 | 0.15 | 0.15 | 0.07 |
| 7  | 15.55 | 0.49 | 395.3 | 1.64 | 0.15 | 0.14 | 0.06 |
| 8  | 15.15 | 0.48 | 394.4 | 1.80 | 0.13 | 0.13 | 0.05 |
| 9  | 15.40 | 0.48 | 372.1 | 1.56 | 0.14 | 0.12 | 0.05 |
| 10 | 15.84 | 0.49 | 386.1 | 2.09 | 0.14 | 0.12 | 0.05 |
| 11 | 15.98 | 0.46 | 390.8 | 2.23 | 0.15 | 0.14 | 0.06 |
| 12 | 16.03 | 0.38 | 364.3 | 2.00 | 0.12 | 0.12 | 0.06 |

All hashtag features (hp, hv, hr) contribute to slightly lowering EG value, as can be seen in Figure 7. Higher hashtag count (hc), on the other hand, can slightly increase EG, as can be seen in Figure 8. The linear trend shows that every 1 hashtag increase will increase EG by +0.0134. In addition, the plot also shows that the best number of hashtags to get the highest EG is 20. All these data show that hashtag tricks do not help a lot in increasing engagement, but post quality does.

Figure 6. Higher number of following and posts lead to lesser EG.
5.3. Contribution of Image Content on EG

To compare between different image content categories, another plot of image contents vs. average EG is shown in Figure 11. According to our data, pictures containing food are the most interesting to users, followed by text images (usually memes or motivational texts) and activity (usually photograph of person/people). The least interesting is talent images, such as people dancing or playing music. Figure 12 shows some examples of each kind of picture. Note that one image can contain some image contents.

5.4. Contribution of Image Assessment on EG

The EG comparison with image assessment features is shown in Table 3. It is shown consistently that higher EG values have higher quality images. In terms of automatic assessment, tech outperforms aest with an average increase of 0.031 between two adjacent levels. In terms of manual assessment, beauty and artistic are the highest performers. Every improvement of image aesthetic by 0.0019, or technical quality by 0.0031, or beauty value by 0.0089, or artistic value by 0.0092, can lead to an increase of EG by 1 level.

5.5. Contribution of User History on EG

Moving on to the user audience features, Figure 13 shows EG as the X-axis and values of ef and eo as Y-axis. It is shown that higher EG values are always caused by a more active audience. Creating more
interesting content, such as improving image quality, can be a way to increase audience activeness.

6. Popularity Prediction

In this section, machine learning regression methods are compared to predict (ER, not EG), as a floating number. Compared to EG, ER is a more usable number since it directly shows the rate of likes. Along with the prediction, features analysis was carried out and discussed in this section. The tested methods are Linear Regression (LR), Random Forest regressor (RF), and Support Vector Regression (SVR).

6.1. Prediction Results

There were challenges in getting some features, i.e., costly human annotation, and extensive API usage to get user history. Thus, in the regression implementation, several combinations of features group were tested and presented to give ideas for future studies.

As the main accuracy measure, $R^2$ (R-squared) was used, along with the error measures, i.e., Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Absolute Error (RAE), and Root Relative Squared Error (RRSE). The methods used were LR, regressor RF, SVR with a radial kernel. All prediction results are shown in Table 4.

Table 4. Regression prediction results (using 10-folds cross validation).

| Features Group | Method | $R^2$ | MAE | RMSE | RAE | RRSE | Best $R^2$ |
|----------------|--------|-------|-----|------|-----|------|------------|
| UPH            | LR     | 0.329 | 2.53| 3.131| 0.806| 0.819| 0.426      |
| UPH, Aa        | RF     | 0.426 | 2.28| 2.901| 0.726| 0.759| (RF)       |
| UPH, Aa, UH    | SVR    | 0.396 | 2.294| 3.003| 0.731| 0.786|           |
| UPH, Aa, UH, Am| RF     | 0.331 | 2.528| 3.127| 0.805| 0.818| 0.427      |
| UPH, Aa, UH, Am| SVR    | 0.397 | 2.284| 2.999| 0.727| 0.759|           |
| UPH, Aa, UH, Am| LR     | 0.516 | 1.931| 2.676| 0.609| 0.7   | 0.648      |
| UPH, Aa, UH, Am| SVR    | 0.648 | 1.697| 2.269| 0.54 | 0.594| (SVR)      |
| UPH, Aa, UH, Am| RF     | 0.641 | 1.671| 2.231| 0.532| 0.604|           |
| UPH, Aa, UH, Am| SVR    | 0.579 | 1.809| 2.492| 0.536| 0.652|           |
| UPH, Aa, UH, Am| LR     | 0.697 | 1.38| 2.112| 0.503| 0.553| 0.731      |
| UPH, Aa, UH, Am| SVR    | 0.731 | 1.464| 1.995| 0.466| 0.522| (SVR)      |

Prediction using only UPH features produced $R^2$ of 0.426, which is simply not enough. The addition of automatic image assessment (UPH, Aa) did not really help either. By adding the user history features (UPH, Aa, UH), the best $R^2$ was increased to 0.648. This group (UPH, Aa, UH) used all readily available features, without the addition of the subjectivity of manual assessment. By adding the manual assessment, the best $R^2$ was increased to 0.731. This shows the rate of likes involves the general characteristics of an image.

6.2. Features Importance

Although the best $R^2$ was acquired from SVR, there is no native way to get features importance for SVR. Thus, another way to achieve this is by calculating the Pearson’s correlation of each feature with ER, as

Figure 13. EG Comparison with engaging followers (ef) and engaging outsiders (eo).

Figure 14. Followers category vs. average and standard deviation of av-er (Global dataset).

Figure 15. Followers category vs. average and standard deviation of av-er (local dataset).
shown in Figure 16, or from RF attribute importance calculation, as shown in Figure 17.

![Figure 16. Features importance based on correlation.](image16)

![Figure 17. Features importance from random forest.](image17)

7. Determinants of Popularity

The correlation (Figure 16) is quite consistent with the RF's features importance (Figure 17). Based on the features importance (section 6) with popularity trend (section 5), it can be concluded that:

- User history features were the most important predictors. These features were used to get the followers demography, particularly how many are active followers, to mitigate the huge deviation of ER, as presented in Figure 14. Thus, history is useful for a future forecast of posts from a particular user.

- Increasing image quality, especially beauty and artistic, can improve ER. For the aesthetic and technical quality (auto values), even though they have a low rank as predictors, the popularity trend shows that improving them still helps in increasing ER.

- There were five user features. Biography length (bl) and link availability (li) did not show significance both in features importance and popularity trend. The number of followers (flr, flrc), posts (pos, posc) and following (flg, flgc) have a quite high rank on predicting ER. Consistent with earlier discussions (Figure 4), that bigger size users (high followers and posts) have indeed lesser ER. Thus, the conclusion cannot be drawn from ER, but from EG. Earlier data in Figure 6 showed that less spammy users (less following and posts) gain higher EG.

- Day (day) and time of post (tf) are significant, as can be seen in RF features importance. Since these features are categorical, the correlation rank (Figure 16) didn't give a suitable result as they were being treated as numerical. Both feature importance and popularity trend show that it is important to pick the best day (Tuesday and Wednesday) and time (00am to 06am) to upload a post in order to raise EG.

- Two post features, i.e., location (lt) and caption length (cl) didn't show significance in both importance and trend. The user tags (ut), on the other hand, can help in increasing EG, as seen in Table 2.

- Among the image content features, pic-food has a higher rank as a predictor. Earlier data in Figure 11 also showed that food pictures get higher EG. Both these data amplify the fact that food pictures are the best pictures to post.

- Increasing hashtags count, as shown in Figure 8, can help in very slightly increasing EG. However, these hashtag features (hp, hv, hr, hc) have a low rank as predictors. This means that engagement is contributed mostly by other factors, not hashtags.

8. Conclusions

In this study, we have done an analysis of popularity trend and prediction on Instagram, using a set of features acquired from user metadata, post, hashtag, image assessment, and user history. In the analysis of popularity trend, EG is used in comparison to respect the lower ER of users with higher followers. In the prediction, ER was used as the output since it is more readable.

It was found that the most important factors in raising EG were image quality, day and time of post, user tags, and type of image. In terms of predicting (or forecasting) ER, the user's history data is very important. The history was used to mitigate the high variability of ERs between users in the global dataset. Compared to the local dataset, the global dataset was proven to have a much higher deviation of ER. Other important features that contributed to ER were image quality, upload day, and time of the post.

Prediction accuracy, measured with $R^2$, can reach up to of 73.1% with all features, and 64.8% without manual image assessment. This accuracy is enough for practical use and has a significance compared to previous studies. Regular users can take advantage of the popularity trend results in determining how to increase likes. Business users can also be benefited in terms of finding influencers for brand marketing.

In future research, the manual assessment values in this study can be changed to similar automated values in order to reduce subjectivity. Other features, such as user history, can still be tuned to get better results. Text analysis features, such as sentiment analysis and concept semantic similarity [26], can also be added to distinguish between popular or less popular posts.
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