CREATING EFFICIENT AND RESOURCE-CONSCIOUS IMAGE-BASED HASHTAG RECOMMENDATIONS WITH THE HELP OF MACHINE LEARNING

Pulok Saha,
Sourav Bhowmik Joy

Computer Science & Technology
Shahjalal University of Science & Techonlogy, Sylhet
Tel.: 01311338931, 01521771459
E-mail: {sourav35joy80, puloksaha.ayon}@gmail.com

Abstract: Hashtag-based image descriptions are a popular approach for labeling images on social media platforms. This systemic Literature Review provides an insight into the system of recommending image-based hashtags. A total of 30 articles were studied all of which contributed to the generation the literature review that follows. On social media platforms, content can be traced using hashtags, therefore making hashtags like a key-pair value in a dictionary. Hashtags are generated by users and different users might come up with different tags for similar posts, due to their different preference and/or community effect. Therefore, it is highly desirable to characterize the users' tagging habits. Machine learning helps in making this method easier. Machine learning is a method of finding patterns in the data, and using it, researchers tend to find and predict relevant hashtags for images in order. In this review we are exploring the possible better solutions through various approaches and expect this study to accelerate the advancement of hashtag recommendation.

Keywords: Hashtag, Images, Machine Learning, Prediction.

1. INTRODUCTION

In the ever-evolving landscape of social media, the use of hashtags has become a ubiquitous means of content categorization and user engagement. Hashtags, denoted by the symbol "#" preceding single words, concatenations, or abbreviations, accompany online images, particularly on platforms like Instagram and Pinterest. These tags serve diverse purposes, ranging from succinctly summarizing the content of a user's post to capturing the attention of followers. [2] [20]For instance, while simple hashtags like *#cat* and *#hill* describe basic objects or locations in a photograph, emotional ones like *#love* convey the user's feelings, and thematic or inferable hashtags such as *#itsfashion* and *#autumn* categorize content or provide contextual information. [29] [33]

Modern techniques for content understanding leverage machine learning algorithms, with deep learning methods like convolutional networks gaining popularity for their impressive performance. However, training these models traditionally relies on extensive sets of manually annotated data, presenting challenges in terms of time and resources.[4] Moreover, such datasets may overlook crucial aspects of image interpretation, such as sentiment, user-centric information, and the dynamic nature of online data distribution.

This paper explores an innovative approach by considering the vast amount of image content online where users have voluntarily associated hashtags. This alternative training data source offers significant advantages, generating large labeled datasets more efficiently than manual annotation and capturing authentic user interests. The focus is on predicting hashtags for images uploaded by specific users, incorporating both image pixel representations and user metadata in the learning process.

Recognizing the extensive variety of classes within images, the paper addresses the challenge of efficiently col-

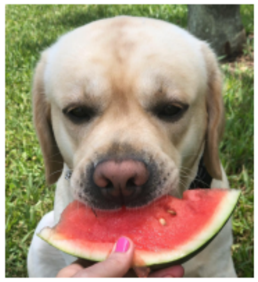
	***Text***: Happy Friday and National Watermelon Day from Paco!! ***Hashtags***: #Friday #paco #nationalwatermelonday #watermelon #bestlabradors #dogsofinstagram #sendadogphoto
	***Text***: Happy National Watermelon Day! Share a watermelon with your dogs to stay cool! ***Hashtags***: #hungrydog #nationalwatermelonday #dogsofinstagram #smile #fundogs #summerlovin

Figure 1: Hashtag recommendations matching with corresponding text.

lecting and annotating data for each class. It proposes algorithms that mimic human cognitive processes, allowing the model to identify objects even when encountering them for the first time. This approach involves extracting information about an object from alternative sources and utilizing it to facilitate identification.

The importance of hashtag usage extends beyond individual expressions to shape trends and influence social media dynamics. [32] While large companies may allocate considerable resources to identify and leverage popular hashtags, small businesses and individual content creators face limitations in adopting similar strategies. This underscores the need for an automated tool capable of analyzing content, suggesting relevant hashtags based on context, and providing a metric for their potential impact on social media. [35]

As we delve into the literature on this subject, it becomes apparent that understanding hashtag dynamics is crucial for effective content dissemination. The following systematic literature review (SLR) aims to comprehensively explore existing research on creating efficient and resource-conscious image-based hashtag recommendations using machine learning. By synthesizing insights from multiple papers, we seek to identify trends, gaps, and potential future directions in this evolving field.

The subsequent part of this paper is structured as follows. Section 2 outlines the methodology employed in this study. The outcomes and discoveries of the research are deliberated in Section 5. Other sections outline related works that have already been completed on this topic and potential avenues for future research endeavors while the review is brought to a conclusion in Section 6.

2. STUDY METHODOLOGY

A literature review aims to provide a comprehensive and unbiased overview of the existing literature focusing on a specific research topic, intended to researchers and practitioners. This document is generated based on several key factors [10] [1] and the research questions outlined below -

1. *How does the use of machine learning in hashtag recommendations align with the current and emerging trends in social media platforms?*
2. *How can machine learning models be optimized without compromising the accuracy of image-based hashtag recommendations?*
3. *What ethical issues can arise in the development and deployment of image-based hashtag recommendation systems, and what steps might be adopted to deal with these?*
4. *How does the proposed recommendation system perform across diverse datasets including various types of contents and what insights can be gained from these evaluations?*
5. *How can advanced image recognition algorithms be used to extract relevant information from visual content and improve the precision of image-based hashtag recommendations?*
6. *Can the developed recommendation system adapt to dynamic changes in user behavior and content types over time, and what strategies are reserved there in order to keep pace with the ever changing social media trends?*

2.1. ***Search Strategy***

Developing a comprehensive search strategy is crucial for identifying relevant literature for a systematic literature review (SLR). Following are some of the important points highlighting the strategies for searching related article and journals [18] -

2.1.1. Identifying key concepts

Everywhere in the literature review, similar search terms were utilized and combined so that a better understanding of the study materials could be attained.

2.1.2. Constructing Search String

After determining the key concepts, keywords and terms, these were combined into relevant search strings, such as -

- Hashtag Recommendation AND Machine Learning
- Photo Sharing Services AND Hashtag Recommendation
- Machine Learning AND Image Sharing OR Hashtag

2.1.3. Source of information

Relevant databases for the study of this hashtag recommendation topic was searched out most of which are mentioned below -

- Scopus
- Google Scholar
- IEEE Explorer

- ACM Digital Library
- ScienceDirect

2.1.4. Refined Searching

Database specific advanced search features were adopted to refine and narrow down the searching scope. Examples include filters for publication date, document type and keywords.

2.1.5. Hand Searching Key Journals

Relevant journals and conference proceedings related to this field were hand searched to get additional articles.

2.1.6. Citation Tracking

Proper citation tracking was ensured to identify seminal papers and other relevant literature.

2.1.7. Iterative Process

- Relevance of retrieved articles were evaluated based on the initial search.
- Search terms based on the initial results were refined and accordingly received feedback was evaluated.

To be more specific and relevant to the study objective, the search procedure was only applied to the journals, book chapters, and conferences published over the last 10 years since social media did not exit at large scale before this timeline and neither did the precious image-based hashtags.

2.2. Inclusion & Exclusion Criteria for articles

2.2.1. Inclusion Criteria

- **Relevance to Image-Based Hashtag Recommendation :** Papers specifically addressing the topic of image-based hashtag recommendations were prioritized.
- **Machine Learning Approaches :** Articles employed with machine learning methodologies, such as deep learning or other relevant algorithms, for the development or enhancement of any type of hashtag recommendation systems were taken into consideration.
- **Publication Type :** Peer-reviewed journal articles, conference papers, and academic publications was considered important as they provide rigorous and scholarly research.
- **Diversity of Approaches :** Studies utilizing a diverse range of machine learning techniques, including but not limited to convolutional networks, recurrent neural networks, and ensemble methods, was considered to provide a comprehensive overview.

- **Application Domains :** Contents (especially images) from various application domains, such as social media platforms, e-commerce, or multimedia content sharing, was included to capture the breadth of image-based hashtag recommendation implementations.

2.2.2. Exclusion Criteria

- **Irrelevant Topics :** Papers that do not specifically focus on image-based hashtag recommendations or do not leverage machine learning techniques for this purpose were not taken into consideration.
- **Insufficient Methodological Detail :** Studies lacking clear descriptions of the machine learning methodologies employed or those with inadequate information on the image-based hashtag recommendation process were easily excluded. [25]
- **Outdated Publications :** Papers published more than ten years ago were excluded to prioritize recent advancements and methodologies in the rapidly evolving field of machine learning for image-based hashtag recommendations.
- **Non-Academic Sources :** Non-peer-reviewed sources, such as blog posts, news articles, and non-academic websites, were excluded to maintain the academic rigor of the literature review.

By applying these inclusion and exclusion criteria, this systematic literature review attempted to ensure the selection of relevant, high-quality research papers that contribute significantly to the understanding of image-based hashtag recommendations system with the aid of machine learning.

3. RELATED WORK

In this section, we delve into the existing research landscape on hashtag recommendation, exploring various methodologies and approaches, particularly those centered around content-based recommendations and personalized recommendations.

*3.1. **Content-Based Hashtag Recommendations***

- Traditional methods analyze users' tagging behaviors, with recent advancements incorporating Convolutional Neural Networks (CNNs) to learn image semantics. [3]
- Notable approaches include using features from existing CNNs or building end-to-end models for collective learning of image and tag semantics [34]

*3.2. **Personalized Hashtag Recommendations***

Distinguish personalized hashtag recommendations, considering users' historical tagging behaviors to implicitly model their preferences. [14] [15] Methods include constructing tag vocabularies, edge prediction in heterogeneous networks, and tensor factorization on user-item-tag tensors. [12] [36] [9]

Figure 2: Overview of images and hashtags in the HARRISON dataset

3.3. *Additional Perspectives from Specific Papers*

- *3.3.1. Harrison Dataset*

Introduces the Harrison dataset for hashtag prediction, emphasizing the need for a benchmark to accelerate hashtag recommendation. The dataset includes 57,383 images from Instagram, each with an average of 4.5 related hashtags.[28]

Collecting Images and Hashtags : In order to enhance the effectiveness of hashtag recommendation systems, emphasis is placed on suggesting hashtags that are widely used in real-world scenarios. To achieve this, a hashtag ranking website was consulted, and a manual selection process resulted in the identification of 50 hashtags from the top 100, chosen based on their semantic relevance. [23] Subsequently, a collection of Instagram photos was gathered for each of the selected hashtags. For each chosen hashtag, a compilation of recent Instagram photos, along with associated hashtags for each photo, was acquired. After eliminating duplicate images, a dataset of 91,707 unique images was obtained, featuring an average of 15.5 associated hashtags per image. The cumulative number of hashtags in this curated dataset reached approximately 1.4 million, spanning 228,200 unique words.

Organizing the Dataset : To create a high-quality dataset, post-processing is carried out on hashtags. Initially, hashtags that include non-alphabetic characters, such as Chinese and Korean characters, are excluded. Subsequently, lemmatization is employed on all hashtags. Lemmatization involves grouping various inflected forms of a word together. For instance, the hashtags walked, walks, and walking are lemmatized to the common base form walk. Through this lemmatization process, duplicate hashtags linked to the same image are eliminated.

Description of the Dataset : Figure 2 shows overall distribution of the HARRISON dataset. The HARRISON dataset has a total of 57,383 images and approximately 260,000 hashtags. Each image has an average of 4.5 associated hashtags (minimum 1 and maximum 10 associated hashtags) due to the removal of infrequently used hashtags.[22] [11]

- *3.3.2. Zero-Shot Classification*

Addresses Zero-Shot Classification and Generalized Zero-Shot Classification, using a restrictive generator to create artificial training models. [5] [26] The study includes comparisons with generative models across

illustration (318)	art (45)	architecture (181)	ootd (94)
drawing (137)	coffee (135)	hollywood (698)	son (502)
boyfriend (30)	tired (13)	vintage (130)	boy (53)
		design (98)	instagood (17)
		losangeles (397)	love (0)
		california (259)	
		yellow (4)	

Figure 3: Examples of the HARRISON dataset, consisting of images and hashtags with encoded class numbers

various datasets.

- *3.3.3. Supervised Machine Learning Algorithms*

  Analyzes the effectiveness of supervised machine learning algorithms concerning precision, learning rate, complexity, and overfitting risks. [30] Provides a general comparison with state-of-the-art machine learning algorithms across different application areas. [19]

- *3.3.4. User Conditional Hashtag Prediction for Images*

  Explores user metadata, such as age and gender, in conjunction with image features from Convolutional Neural Networks (CNNs) for hashtag prediction. The method leverages user-defined context information. [6]

This overview highlights the breadth and depth of research in the field, covering various aspects of content-based and personalized hashtag recommendations. The literature review serves as a foundation for understanding existing methodologies, gaps in research, and potential avenues for further exploration in the quest to create efficient and resource-conscious image-based hashtag recommendations through machine learning.

4. DATA EXTRACTION & ANALYSIS

4.1. Data Collection

- **Source & Categories :** Images were collected from various social media platforms using Instaloader. Ten distinct classes were defined based on popular topics found on Instagram, including animals, art, fashion, fitness, flowers, food, instagood, nature, selfie, and sports.
- **Quantity and Quality Assurance :** Papers made various approaches for collecting quality images of different types.[29] However each class consisted of around 800 images, ensuring a diverse and representative dataset. A robust data collection method was employed to guarantee accurate and well-described statistics, forming the foundation for subsequent decisions.

4.2. Data Cleaning

- **Noise Reduction :** After data collection, a meticulous cleaning process was undertaken to eliminate unnecessary or noisy data. Each class was scrutinized, and unwanted data that wasn't properly categorized was identified and removed.[8][7]
- **Consistency :** Ensured consistency with other datasets by addressing inconsistencies arising from user input errors, corrupted data, and variations in data definitions across sources. Data cleaning was tailored to fit the unique characteristics of each dataset.
- **Outlier Identification :** Utilized transfer learning as a classification method, focusing on identifying noisy images by measuring their distance from centroids. Images exceeding a defined threshold (two standard deviations from the mean) were considered noisy and subsequently removed.

4.3. Data Processing

Several papers employed various methodology and Machine Learning algorithms to process the collected data in order to find out a pattern from the models using vivid datasets. Some of the most used methods are discussed below -

- **Transfer Learning with VGG-19 :** Processed cleaned data using transfer learning with VGG-19, a convolutional neural network (CNN) algorithm renowned for its efficacy in various computational tasks. VGG-19 automatically analyzes spatial hierarchies of features through backpropagation, employing convolutional layers, fully connected layers, and pooling layers.[29]
- **Data Classification :** VGG-19, a dominant class in deep neural networks, was employed for image classification. It is widely used in image recognition tasks such as image classification, object detection, and face recognition. Transfer learning facilitated the classification of images into predefined classes.
- **Extension to CNN :** Extended the CNN methodology, incorporating transfer learning to train data classes effectively. This approach is particularly useful for classifying problems and regression problems in image recognition, leveraging nearest training sets in the feature space.
- **Supervised Learning :** Employed a supervised learning method to train the collected data. The training model categorized images into classes based on associated hashtags. The model included parameters such as epoch, batch size, and learning rate. [30]

5. Data Analysis & Result

Almost all of the studied papers and journals [24] [13] trained a model based on the collected data which is capable of suggesting hashtags based on images. However there were varities in the methods obtained for displaying the outputs described by respective papers for the users. Some of the common output presentation processes are discussed below -

- **Transfer Learning with TensorFlow.js and HTML Integration :** For hashtag prediction, some papers implemented Transfer Learning [27]using TensorFlow.js [1]. and HTML for seamless integration with the frontend to showcase the results. The process began with the acquisition of images from Instagram using Instaloader, resulting in a dataset of around 5000 images.

[1] `https://www.tensorflow.org/`

Subsequently, the images were preprocessed, leading to ten classes with approximately 700 images in each. Transfer learning was chosen for training due to its compatibility with limited datasets and demonstrated efficiency. The trained model was then converted into TensorFlow.js, allowing it to be loaded onto the webpage alongside HTML and CSS.

The final framework incorporated small batches of transfer learning for training and testing, enabling the prediction of hashtags for various images. Users could upload an image on the website's homepage, and upon clicking "predict," hashtags were fetched and accurately predicted, with the output displayed on the webpage.

Figure 4: Figure showing the predicted hashtags for the uploaded image

- **Comparative Effectiveness Analysis :** Several papers opted for a comparative analysis of the proposed method against existing approaches. Precision, recall, and F1-score were the evaluation metrics, plotted against the number of hashtags returned by recommendation methods. The proposed MACON method exhibited significant improvements across all three metrics compared to competitors. Notably, when compared with the best competitor CoA, MACON achieved absolute improvements ranging from 12.8% to 23.6% in precision, 8.6% to 20.8% in recall, and 10.7% to 13.4% in F1-score. The analysis included a comparison with various methods, such as ImgAtt, T2W, TLSTM, and personalized FM-IC. Further, the study conducted a performance gain analysis by considering different components of the proposed method, emphasizing the importance of content modeling and user habit modeling for recommendation accuracy.

- **Performance Gain Analysis :** The authors conducted a meticulous analysis of the proposed method, MACON, focusing on three crucial components: text input, image input, and user habit modeling [2]. To highlight the significance of the user habit modeling module, they introduced variants of MACON, namely MACONt+i, MACONi+h, and MACONt+h, by selectively removing or retaining certain components. [37]

  Firstly, MACON exhibited superior performance compared to MACONt+i, emphasizing the critical role of the habit modeling module. The absolute improvements ranged from 9.3% to 16.5% in F1-score when the parameter K varied from 1 to 9. Notably, MACONt+i even outperformed CoA by up to 16.8%, underlining the efficacy of the adopted parallel co-attention for services where both image and text contribute significantly to tagging.

  Secondly, MACON outperformed both MACONt+h and MACONi+h across all metrics, indicating the collective utility of text and image inputs for hashtag recommendation. The average relative F1-score improvements over MACONt+h and MACONi+h ranged from 7.6% to 15.6%, emphasizing the substantial enhancement in recommendation accuracy achieved through hybrid modeling.

[2] The code of the proposed method is publicly available at `https://github.com/SoftWiser-group/macon`.

Thirdly, in comparison with the TLSTM method, MACONt+h demonstrated absolute improvements ranging from 10.8% to 15.8% in F1-score. This further affirmed the effectiveness and applicability of the proposed user habit modeling module, positioning it as a valuable addition to the field.

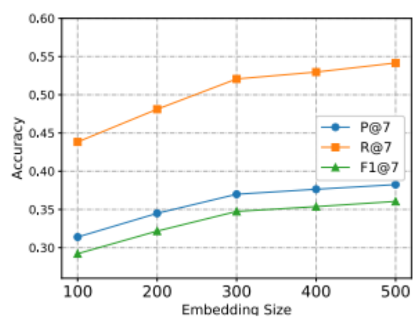
top-K	MACON			MACON$_{t+i}$ (text+image)			MACON$_{t+h}$ (text+habit)			MACON$_{i+h}$ (image+habit)		
	P@K	R@K	F1@K	P@K	R@K	F1@K	P@K	R@K	F1@K	P@K	R@K	F1@K
1	0.636	0.214	0.270	0.384	0.060	0.105	0.596	0.196	0.248	0.560	0.171	0.221
3	0.493	0.375	0.341	0.300	0.142	0.193	0.457	0.340	0.311	0.441	0.305	0.289
5	0.415	0.454	0.346	0.259	0.204	0.228	0.388	0.418	0.320	0.379	0.382	0.305
7	0.370	0.521	0.347	0.231	0.255	0.243	0.360	0.503	0.337	0.337	0.437	0.307
9	0.334	0.566	0.340	0.210	0.298	0.247	0.311	0.517	0.314	0.307	0.481	0.305

Figure 5: The performance gain analysis. Both hybrid content modeling and user habit modeling are useful to improve recommendation accuracy.

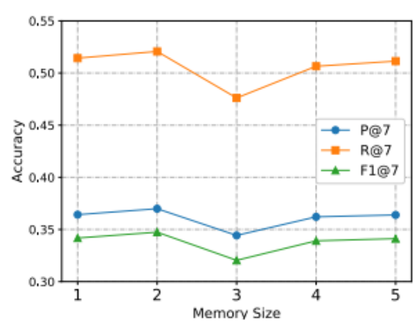
- **Parameter Sensitivity Study :**The authors of the some papers [34] [37] delved into a parameter sensitivity study, focusing on the embedding size (d) and memory size (L) in their method, MACON. Their objective was to understand how these parameters influence recommendation accuracy.

  For the embedding size (d), the authors varied it from 100 to 500, observing notable performance improvements as d increased. However, diminishing returns were noticed beyond a certain threshold, specifically from 400 to 500. Considering the trade-off between computational resources and performance gain, they opted for an embedding size of d = 300.

  Regarding the memory size (L), representing the historical posts selected to model a user's tagging habit, variations from 1 to 5 showed relatively stable performance. Consequently, they fixed the memory size at L = 2 for their experiments.



(a) The effect of the embedding size d



(b) The effect of the memory size L

Figure 6: The parameter sensitivity study. The performance of MACON increases as d increases, and stays relatively stable as L varies. We fix d = 300 and L = 2 in this work.

- **Accuracy metrics for VGG-19 model :** Many of the articles [29] that used VGG-19 as their fundamental model for predicting hashtag suggestions included various accuracy evaluation metrics namely, confusion matrix, loss function etc to measure the performance given by their respective models.

  One of the articles published from International Journal of Engineering Research & Technology (IJERT) listed their model accuracy parameters as such -

5.1. Confusion Matrix for non-normalized VGG-19

The confusion matrix for non-normalized VGG-19 prediction used in this paper has a definitely high accuracy that ranges to about 68%, as seen from the graph below (fig. 7). The loss observed has always been kept minimal to ensure accurate predictions.

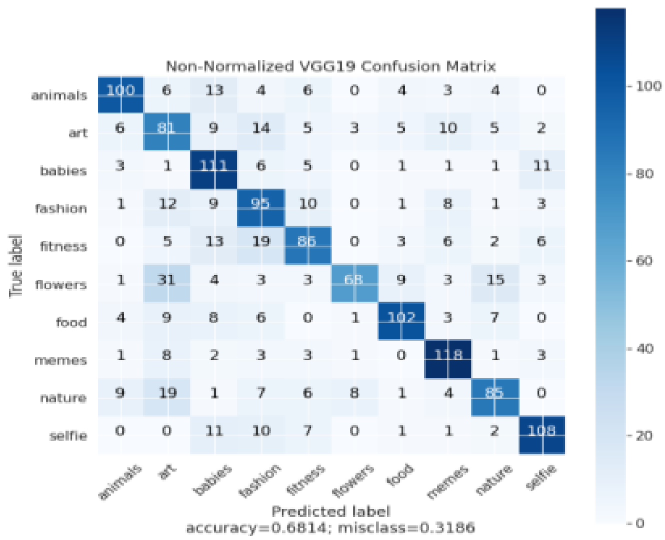


Figure 7: Figure showing the confusion matrix for non-normalized VGG-19.

5.2. Confusion Matrix for normalized VGG-19

The confusion matrix for normalized VGG-19 (fig. 8) is quite similar to the non-normalized one with respect to accuracy and misclass and also matching true and predicted labels.

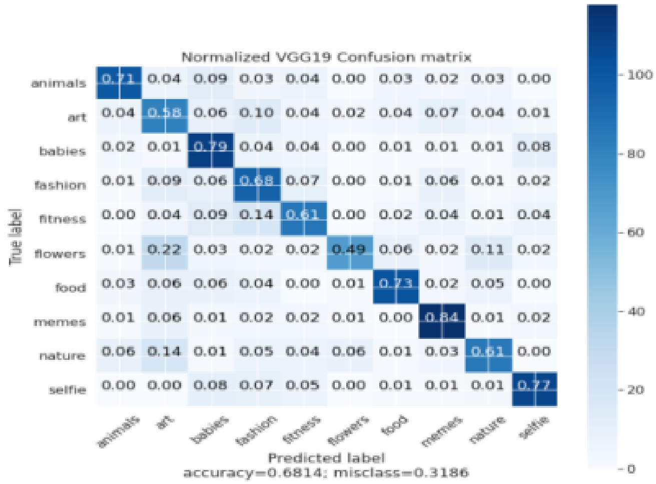


Figure 8: Figure showing the confusion matrix for normalized VGG-19.

5.3. Loss Function

The model's loss function was obtained using the train data and is shown in fig. 9. The model loss for test data has been limited to be as low as possible.

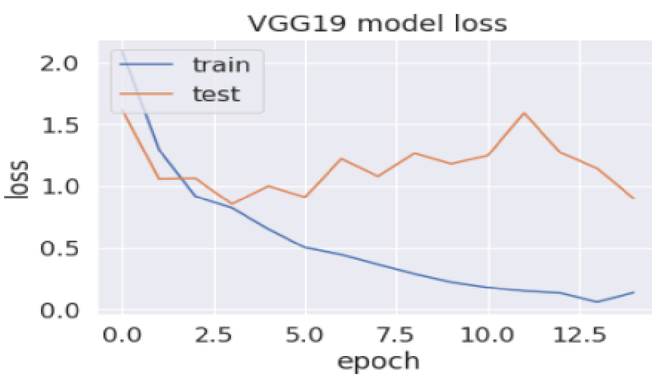


Figure 9: Figure showing the train and test curve for model loss using VGG-19.

5.4. Model Accuracy

When final model accuracy was computed, it provided the following result as shown in fig. 10. The accuracy score has been maintained to be as high as possible upto 68.14%.

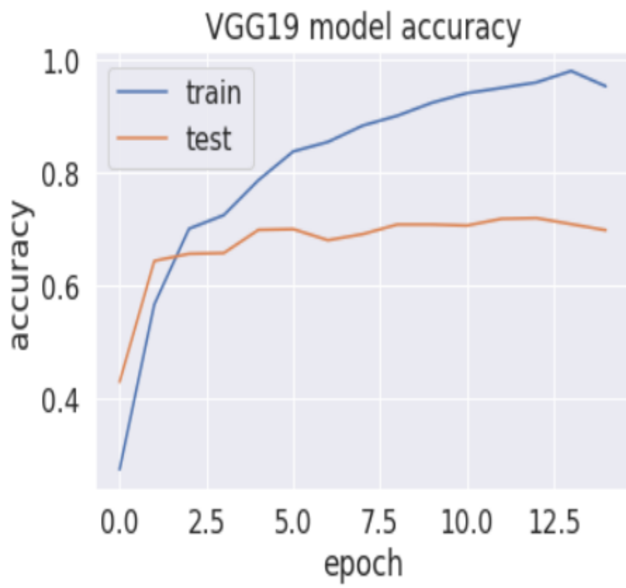


Figure 10: Figure showing the train and test curve for model accuracy using VGG-19.

Thus it can be concluded that this particular paper and their chosen model was correct to a large scale in predicting appropriate hashtags from images.

6. Discussion

This systematic literature review on hashtag recommendation combines insights from numerous journals and papers. Since this trend of posting/using hashtags on images on social media platforms is a very recent one, research interest in this particular sector has not yet caught attention of keen learners and graduates. There are only a few journals and papers available for rigorous study of this topic.[17] [21] However following is a discussion about some of the key findings that we obtained and the limitations of this literature review.

6.1. Key Findings

Our study revealed that meticulous data collection and cleansing yield excellent results. Building an end-to-end image-based hashtag recommendation system using machine learning, including CNN, KNN, and transfer learning, was a valuable learning experience. However, deep learning methods may face challenges with data requirements. Future steps involve enhancing classification accuracy, particularly in fully supervised approaches. In this era of social media, image-based hashtag recommendations can go on to be a newer and interesting side of Machine Learning based research topic. A summary of several papers [31] [16] is attached in the following table -

Objectives	Methodology/ Models Used	Result/ Outcomes	Dataset	Drawbacks
Recognising objects at the very first look and trying to generate hashtags for real-world objects. For the evaluation of the photos, a bottomline framework is used, which consists of visual feature extraction based on CNN.	CNN, VGG-Object, VGG-Scene	In this work, on applying two visual features, object-based features and scene-based features, the baseline models were evaluated.	Harrison	With only a few images, not too many categories can be seen, which will not be very beneficial in real-world applications.
This work not only tells how training and newer data need not be in the same space, but also talks about progress of TL in classification, regression etc.	Transfer learning, ML, Data mining	This work suggests "what to transfer" and "when to transfer". Also, it proposes where improvement needs to be made, like negative transfer, different feature spaces etc		Transfer learning is not applied on all of the ML algorithmic models. Only three models are taken into consideration here.
In this paper, generating hashtags are introduced from images online. Here, ML is used to predict hashtags for realistic images and makes choices and branding much easier.	Zero-shot classification, Supervised ML algorithms, ImageNet classification, DCNN	This work has an accuracy of about 85generates multiple hashtags for a single image. These hashtags can be directly used in social media accounts like Instagram, Facebook, Twitter etc. to	Harrison	Very few categories have been classified in the Harrison dataset, and on using the same, this work does the same. Also, some images have a few hashtags for a number of images (around 2).

Tabla 1: COMPARISON AND ANALYSIS OF DIFFERENT PAPERS

6.2. Review Limitations

While this review study endeavors to offer a comprehensive exploration of hashtag recommendation from images, certain limitations warrant acknowledgment. Primarily, the selection of the primary literature set adheres to specific search criteria outlined in the methodology section. However, this approach may inadvertently omit relevant papers that could contribute valuable insights. The possibility of enhancing the inclusivity of the review by employing alternative search methodologies remains an avenue for future investigations.

Moreover, the study acknowledges limitations in data extraction accuracy and potential misclassification during the implementation of the proposed models. A secondary review was conducted to mitigate these risks, underscoring the commitment to refining the quality of data and classifications. Despite these limitations, this study contributes valuable insights on hashtag recommendation system from images, paving the way for future research endeavors to address and overcome these challenges.

References

[1] The prisma 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, 88:105906, 2021.

[2] Yong-Yeol Ahn, Filippo Menczer, Alessandro Flammini, and Le Weng. Virality prediction and community structure in social networks. *Scientific Reports*, 3(2522), 2013.

[3] Anna Beketova and Ilya Makarov. Instagram hashtag prediction using deep neural networks. In Ignacio Rojas, Gonzalo Joya, and Andreu Català, editors, *Advances in Computational Intelligence*, pages 28–42, Cham, 2021. Springer International Publishing.

[4] Asma Belhadi, Youcef Djenouri, Jerry Chun-Wei Lin, and Alberto Cano. A data-driven approach for twitter hashtag recommendation. *IEEE Access*, 8:79182–79191, 2020.

[5] Maxime Bucher, Stephane Herbin, and Frederic Jurie. Generating visual representations for zero-shot classification. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV) Workshops*, Oct 2017.

[6] Emily Denton, Jason Weston, Manohar Paluri, Lubomir Bourdev, and Rob Fergus. User conditional hashtag prediction for images. KDD '15, page 1731–1740, New York, NY, USA, 2015. Association for Computing Machinery.

[7] Rajmadhan Ekambaram, Sergiy Fefilatyev, Matthew Shreve, Kurt Kramer, Lawrence O. Hall, Dmitry B. Goldgof, and Rangachar Kasturi. Active cleaning of label noise. *Pattern Recognition*, 51:463–480, 2016.

[8] Rajmadhan Ekambaram, Dmitry B. Goldgof, and Lawrence O. Hall. Finding label noise examples in large scale datasets. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2420–2424, 2017.

[9] Xiaomin Fang, Rong Pan, Guoxiang Cao, Xiuqiang He, and Wenyuan Dai. Personalized tag recommendation through nonlinear tensor factorization using gaussian kernel. *Proceedings of the AAAI Conference on Artificial Intelligence*, 29(1), Feb. 2015.

[10] User History Features. Instagram post popularity trend analysis and prediction using hashtag, image assessment, and. *The International Arab Journal of Information Technology (IAJIT)*, 18(01):85 – 94, 1970.

[11] Li Fei-Fei and Andrej Karpathy. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, CVPR '15, pages 3128–3137, 2015.

[12] Wei Feng and Jianyong Wang. Incorporating heterogeneous information for personalized tag recommendation

in social tagging systems. KDD '12, page 1276–1284, New York, NY, USA, 2012. Association for Computing Machinery.

[13] Y. Gong, Y. Jia, T. Leung, A. Toshev, and S. Ioffe. Deep convolutional ranking for multilabel image annotation. 2013.

[14] Yunchao Gong, Qiuhong Ke, Michael Isard, and Svetlana Lazebnik. A multi-view embedding space for modeling internet images, tags, and their semantics. *International Journal of Computer Vision (IJCV)*, 106(2):210–233, 2014.

[15] Ziwei Guan, Jiajun Bu, Qiaozhu Mei, Chun Chen, and Can Wang. Personalized tag recommendation using graph-based ranking on multi-type interrelated objects. In *SIGIR*, pages 540–547. ACM, 2009.

[16] Tomasz Hachaj and Justyna Miazga. Image hashtag recommendations using a voting deep neural network and associative rules mining approach. *Entropy*, 22(12), 2020.

[17] Allan Hanbury. A survey of methods for image annotation. *Journal of Visual Languages Computing*, 19(5):617–627, 2008.

[18] Joshua D. Harris, Carmen E. Quatman, M.M. Manring, Robert A. Siston, and David C. Flanigan. How to write a systematic review. *The American Journal of Sports Medicine*, 42(11):2761–2768, 2014. PMID: 23925575.

[19] M. Hasan, E. Agu, and E. Rundensteiner. Using hashtags as labels for supervised learning of emotions in twitter messages. In *ACM SIGKDD Workshop on Health Informatics*, 2014.

[20] Haoran Huang, Qi Zhang, Yeyun Gong, and Xuanjing Huang. Hashtag recommendation using end-to-end memory networks with hierarchical attention. In Yuji Matsumoto and Rashmi Prasad, editors, *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 943–952, Osaka, Japan, December 2016. The COLING 2016 Organizing Committee.

[21] S. J. Hwang and K. Grauman. Learning the relative importance of objects from tagged images for retrieval and cross-modal search. *International Journal of Computer Vision*, 100(2):134–153, 2012.

[22] Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015.

[23] Ralf Krestel, Peter Fankhauser, and Wolfgang Nejdl. Latent dirichlet allocation for tag recommendation. In *Proceedings of the Third ACM Conference on Recommender Systems*, RecSys '09, page 61–68, New York, NY, USA, 2009. Association for Computing Machinery.

[24] Kok Wai Lim and Wray Buntine. Twitter opinion topic model: Extracting product opinions from tweets by leveraging hashtags and sentiment lexicon. In *Proceedings of the 23rd ACM International Conference on Information and Knowledge Management (CIKM)*, pages 1319–1328, 2014.

[25] T. J. Meline. Selecting studies for systemic review: inclusion and exclusion criteria. *CICSD*, 2006. `https://doi.org/10.1044/cicsd_33_s_21`.

[26] Mohammad Norouzi, Tomas Mikolov, Samy Bengio, Yoram Singer, Jonathon Shlens, Andrea Frome, Greg S. Corrado, and Jeffrey Dean. Zero-shot learning by convex combination of semantic embeddings, 2014.

[27] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10):1345–1359, 2010.

[28] Minseok Park, Hanxiang Li, and Junmo Kim. Harrison: A benchmark on hashtag recommendation for real-world images in social networks, 2016. `https://arxiv.org/abs/1605.05054`.

[29] Taurunika Shivashankaran, Prajwal Bharadwaj N, Prajwal K, Madhushree S, and Sachin D N. Prediction of hashtags for images. *IJERT*, 2020. `https://www.ijert.org/prediction-of-hashtags-for-images`.

[30] Amanpreet Singh, Narina Thakur, and Aakanksha Sharma. A review of supervised machine learning algorithms. In *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, pages 1310–1315, 2016.

[31] Nischitha N Shashank Bharadwaj R Ravi Kumar V Tanuja Kayarga Sudeep S, Suchethana Swaroopa P N. A survey on hashtag generation and prediction for images and text. *IJERT*, 17-07-2021. `https://www.ijert.org/a-survey-on-hashtag-generation-and-prediction-for-images-and-text`.

[32] Oren Tsur and Ari Rappoport. What's in a hashtag? content based prediction of the spread of ideas in microblogging communities. In *Proceedings of the Fifth ACM International Conference on Web Search and Data Mining*, WSDM '12, page 643–652, New York, NY, USA, 2012. Association for Computing Machinery.

[33] W.L.A.T.A.L Weerasooriya. Hashtags prediction for image post in social networks. *UCSC : University of Colombo School of computing*, 3-Aug-2021. `http://dl.ucsc.cmb.ac.lk/jspui/handle/123456789/4380`.

[34] Qi Zhang Yuyun Gong. Hashtag recommendation using attention-based convolutional neural network. *IJCAI-16*, 2016.

[35] Eva Zangerle, Wolfgang Gassler, and Günther Specht. Recommending #-tags in twitter. 2011.

[36] Qi Zhang, Yeyun Gong, Xuyang Sun, and Xuanjing Huang. Time-aware personalized hashtag recommendation on social media. In Junichi Tsujii and Jan Hajic, editors, *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, pages 203–212, Dublin, Ireland, August 2014. Dublin City University and Association for Computational Linguistics.

[37] Suwei Zhang, Yuan Yao, Feng Xu, Hanghang Tong, Xiaohui Yan, and Jian Lu. Hashtag recommendation for photo sharing services. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(01):5805–5812, Jul. 2019.