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Multi-label Convolution Neural Network for Personalized News Recommendation based on Social Media Mining

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Prediction of user's multi label interests and recommending the users interest based popular news articles through mining the social media are difficult task in Hybrid News Recommendation System (HYPNRS). To overcome this issue, this study proposes a deep learning approach - Multi-label Convolution Neural Network for predicting users' diversified interest in 15 labels using the binary relevance method. Based on labels of user's interest, the most popular news articles are determined and their labels were clustered by mining social media feeds Facebook and Twitter along with current trends. The reliability of retrieved popular news articles also verified for recommendation. Eventually, the latest news articles catered from news feeds integrated along popular news articles and current trends together provide a recommendation list with respect to user interest. Experimental results show the proposed method diversified users interest labels prediction performance improved 5.87%, 12.09%, and 18.49% with the following state of art Support Vector Machine (SVM), Decision Tree and Naïve Bayes. The recommendation performance concerning users' interest achieved 90%, 93.3%, 90% with social media feeds Facebook, Twitter and News Feeds accordingly.

Keywords: Classification, Deep learning, Recommendation, Social media

Introduction

With the headway of World Wide Web (WWW), the news perusing style of individuals has progressively transformed from the ordinary media like Television, Printed Newspaper to web[1]. Now a days, reading online news articles has become a common activity for most of us, because the WWW provides plenty of news articles from diversity of resources. The individuals obtain the news articles on a daily basis round the clock. At the same time, however, it's a troublesome task for them to find relevant news articles, due to abundance of news articles generated from several news sources. To alleviate this information overload problem, news recommendation becomes a crucial task for online news providers.

The individuals are topic-sensitive in reading news articles because they are generally interested in several news labels for e.g. (sports, entertainment etc.).[2] So, it's a typical key challenge to predict the users' interest in multiple news labels based on their diversified reading history from their user profiles. In addition to that, now-a-days most of the people get news articles via social media feeds without considering news portals. This is so considering hot news popping up becomes viral immediately in social media. Social media act as an open platform for discussing news articles and real-world events by the general population.[3] This open platform discussion helps distinguishing between the most prominent and most popular news articles, and happening all around the world. So, people are interested in getting access to fresh and popular news articles. It is, therefore, necessary to design a system that recommends fresh and popular news through mining the social media feeds e.g. Twitter and Facebook appertaining to users' diversified interests. In this study, a deep learning mechanism was presented to predict users' interests with the help of machine learning and deep learning technologies as they produce noteworthy developments in various applications in the last few years. Natural Language Processing such as Emotion Recognition[4, 5] and Cyber Security[6] are few to be important for recommendation system. Recently, deep learning has brought in a revolution into a recommendation system for customer satisfaction.[7] The deep learning-based recommender system has attained high recommendation quality because it provides significant attention to overcome the

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obstacles that prevail in the conventional model. Unfortunately, only very small attention is found on news recommendation system using deep learning. So, in this paper, a deep learning mechanism – Convolution Neural Network[8] was applied for multi labels users' interest prediction. Most of the existing systems[9,10] suggest the news articles emphasis on the user's interest. They did not concern about recommending the popular and trendy news articles by the way of social media mining. Some of the researchers have identified this issue, they concerned about the popular news articles recommendation via mining Twitter feeds.[11–13] The popularity of Twitter has given additional weightage along with personalization to make the users instantly updated. In addition to that, in this proposed work, the most popular news articles are determined not only from Twitter feeds but also from Facebook feeds. Because, nowadays, many people encountered the trending news articles in Facebook. It was shared from numerous sources such as news feeds, twitter and several groups also could be shared to other sources e.g. WhatsApp messenger, Facebook messenger, groups and get the number of likes as well in Facebook. Similarly, people keep on sharing and posting likes to the news articles to their friends, friends of friends etc. So, this chain of the network grows infinitely reaches to billion sometime. Therefore, Facebook becomes the best mode for determining the trending news articles.[13] But, we could not trust all the trending news articles propagated via social media in the forms of likes. It is undoubtedly challenging task to identify the fake news articles.[14] Many researchers concentrate on detecting the fake news article using various classification techniques.[15–17] It is also good to detect the fake news articles via classification, but it must be verified in International Fact Checking Network (IFCN). IFCN is a worldwide growing community of fact-checkers to identify viral misinformation. It promotes fact-checking world-wide collaborated with 100 organizations. Hence, in this article, the most popular news articles were identified from Twitter and Facebook feeds and also verified in IFCN.

The major contributions of this work are summarized as follows

1. Deep learning-based approach to predict 30,000 Yahoo! users' diversified interest in fifteen labels from 13,346 features from user profile dataset by implementing a novel architecture of Multi label Convolution Neural Network.
2. Retrieving the most popular news articles and its labels analysed by harnessing Facebook and Twitter feeds along with current trends also verified in IFCN.
3. The recommendation of the latest news articles from Really Simple Syndication (RSS) feeds and retrieved most popular news articles vis-a-vis users' interest labels.

Related Works

Commonly, the recommendation systems play a significant impact in various application of e-commerce.[18] They help individuals in making decisions such as which things to buy (item recommendation)[19], which kind of news articles to be read (news recommendation),[20] which music to listen (music recommendation),[21] which film to watch (movie recommendation)[22] etc. Thus, the systems are of great help in abridging the information overload problem. In contrast to all the above-mentioned recommender systems, news recommender system possesses some distinct challenges. It connects and updates people with outside world instantly, and also suggests the news articles tailored to their interests.

The user's interest can be captured from the user profile, which evolves over time. The user profile can be created or maintained through either explicit feedback in the form of like or dislike or ratings posted by the users, or else implicit information by the way of analysing the users browsing history (click behaviour).[23] Many researchers have either used implicit or explicit user profile for predicting users interest category using different techniques for the personalized news recommendation. Liu *et al.*[24] have presented a Bayesian model via analysing user's histories to predict users' interests. They conducted experiments on Google sites (live traffic) and attained good recommendation results. Billsus *et al.*[25] proposed a novel approach which predicts users' long term and short interest using multi-strategy machine learning approaches, namely, Naïve Bayes classifier and Nearest Neighbour algorithm. Manoharan *et al.*[26] proposed fuzzy logic-based methodology (MFIS-Mamdani Fuzzy Inference System) for predicting label wise users' interest.

Bai *et al.*[27] developed a novel approach for predicting users interest via analysing implicit profiles of the users. They built the user profile through analysis of user's search history and their interaction with news site.

Pengtao *et al.*[28] have presented a SCB algorithm to capture dynamic users' interest which evolves over time. They also concentrated multi-dimensional features of news fields.

Sahin Albayrak *et al*.[29] suggested a news recommender system based on incorporating trends and temporal user habits for recommendations. They predicted dynamic users' interest and trends by analysing users implicit-click through probability from three news portals.

Zheng *et al*.[30] proposed RL (Reinforcement Learning) for predicting users' interest from implicit users' data. This method was effective in modelling the dynamic news feature and user preferences.

In our proposed work, the user’s interest is captured by analysing their implicit behaviour on Yahoo! site using Deep learning approach- Convolution Neural Network for personalized recommender system. Moreover, it is necessary to incorporate popularity and trends of social media to improve the personalized recommender system. This is because people are more inclined to social media for obtaining news articles. Considering the focus of many researchers is on social network site, namely, Twitter for identifying trendy news articles. Nirmal *et al*.[31] integrated social media Twitter to improve the personalized news recommendation system via identifying the popular news articles in Twitter. Natarajan *et al*.[32] have suggested news recommendations depending on trends, popularity, and preferred Location. They determined popular and trend news articles using the Twitter to provide good recommendations. In our perspective, none of the research works focus on obtaining popular news articles from the Facebook to improve popularity based personalized recommendation. So, we have addressed this challenge to improve the personalized news recommendation system and also verified the reliability of the news articles for effective recommendation.

Materials and Methods

The proposed framework comprises the following contribution, namely predictions of Yahoo! users' diversified interest using deep learning approach- Multi-Label Convolution Neural Network (MLCNN) from 13,346 features and 15 labels from Yahoo! A4 dataset. This data set was pre-processed using pre-processing techniques such as data cleaning, data transformation, data integration, and data sampling and reduction for prediction purposes. Further, the pre-processed data fed for MLCNN for predicting users diversified label specific interest. Based on users' interest predicted label, the most popular news articles were identified by the way of mining social media feeds Twitter and the Facebook along with current trends and validated the trust worthiness of the news articles. Besides that, the breaking news articles were also retrieved with respect to users label specific interests. Before recommending it, the redundancy was removed, in case of same user’s interest label present in the current trends. The overall architecture of proposed HYPNRS framework based on social media mining is shown in Fig. 1.

Data Pre – Processing

The Yahoo! A4 dataset was pre-processed using the following pre-processing techniques.

Data Reduction

This method is used to reduce the large volume of the data in the dataset. Because this user profile dataset contains 1,589,113 user profiles, 13,346 features along with 380 labels. This data was extremely large. From this number of training, samples were taken for 30, 000 user profiles and labels were also reduced to 15. Because, if the number of user profiles are tremendous, then training time will be more using deep learning mechanism. Moreover, mining of these much-labelled data from social data and news feeds data may take a very long time and highly impossible. Hence, the labels were reduced to 15 in this dataset

In this way, the training samples and labels were reduced in this dataset. Further, this data fed for the cleaning process.

Data Cleaning

This method is used to clean the data in the dataset which was incomplete. It means that some features have no value in the dataset. Similarly, labels associated with the feature vectors are also empty. To make the dataset complete, the features as well as label present in the dataset should be fulfilled properly. It was done in the following way.

Features Side Cleaning

The features side cleaning was done by applying the missing value imputation K-nearest neighbour model. The missing values of target samples were imputed by finding the samples which are closest to it and by taking an average of nearby points to fulfil target sample missing value.

Label Side Cleaning

The features were associated with the root label almost all the tuples in this dataset were complete.

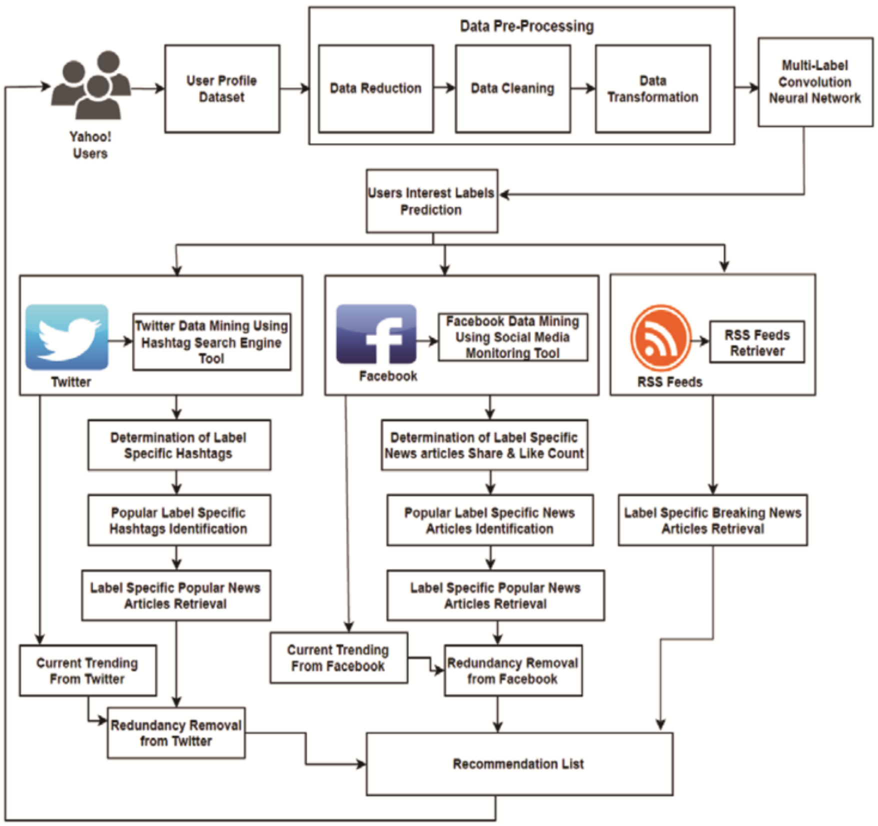

Fig. 1 — Architecture of proposed HYNRS framework based on social media mining

Sometimes in few cases, the root label was not present, and then the entire tree structure was traversed to check the presence of any child nodes in the corresponding root label. If so, then the assumption made that the user is interested in a specific label. For an instance, if the users have shown interest in football, then the assumption was made that the user is interested in sports label. On other hand, none of the sub-labels were found certain user profiles. Then, the assumption was made as the user is not interested in that label. In this way, the features and labels were fulfilled to make the dataset ready for transformation purposes.

Data Transformation:

The following data transformation technique was applied before fed into MLCNN.

Normalization:

This technique was used to transform the data into [0–1] range using the normalization technique. The most common way to normalize the data is Min-Max normalization. The input features were scaled through Eq. 1

$$zi = (xi - \min(x))/(\max(x) - \min(x)) \quad \ldots (1)$$

This normalized data is ready to be fit enough for an efficient prediction process, but normalized features should be arranged in the following way before fed into CNN.

Dataset Features Position Arrangement:

In this step, the related features should be placed nearby to share similar information for feature extraction purposes in CNN in the entire dataset. Related features mean that the properties of features should be related to one another. For instance, ad view, ad click, ad scroll time, number of seconds ad watching, etc. should be placed nearby for making local connectivity between the dataset. Hence ad relevant information can be shared between the features. Moreover, not only for information sharing, it was also used for analysing the important features for classification purposes.

The above mentioned all the procedures repeated for all the 15 labels to pre-process the data and fed for label wise users interest prediction using MLCNN

Proposed Methodology

While there are several approaches available for multi-label classification, this proposed work insight on Multi-label Classification using the Convolution Neural Network (CNN). CNNs are the most efficient supervised deep learning method which produces a significant impact in the last couple of years due to an increasingly wide range of real-world applications.[33] Concerning the proposed work, the number of features was more in this dataset. Therefore, the classification task is quite complex by using normal machine learning models. So, CNN was best for classification purposes. It was able to do automatic feature extraction along with the classification process.[34] Hence, in this proposed work, a multi-label classification was developed on top of CNN for predicting the user's interest for fifteen labels using the binary relevance method. In this method, once the CNN architecture was designed for one label, the same model could apply to other labels as well.

The following Section discusses CNNs and their application to predict user's interest in a multiple labels.

Multi Label Convolution Neural Network

The user profile input features of size 13,346 transformed into a 3-dimensional matrix were 115 × 116 × 1 where "115" represents the width, "116" represents the height, and "1" represents the depth of the features placed in the input layer for every user and every label as well. This layer was used to pass the input user profile feature vectors 115×116×1 into the Convolution layer. Here, we have used 3 Convolution layers (CONV1, CONV2, and CONV3), 3 Max Pooling layers (PL1, PL2, and PL3), one Dense Layer (DL), and one output layer summarized in Table 1. The max Pooling layers (PL1, PL2, and PL3) were kept behind after each convolution layer (CONV1, CONV2, and CONV3). The convolution operation was applied in the input layer with kernel size 3×3 and stride set at 1 and the convolved features with dimension 113 ×114 × 2 were obtained through Eq. 2.

$$\mathrm{CF} = \left[\frac{\mathrm{w}-\mathrm{F}+2\mathrm{P}}{\mathrm{s}}\right] + 1 \quad \ldots (2)$$

Here, CF = Convolved Feature, F = Size of Filter, W = Input Size, P = Padding, S = Stride

These features were passed via ReLU Activation function which is max {0, x}. Then, Max Pooling operation (PL1) was applied to the obtained convolved feature along with kernel size 2 × 2 and the output dimension was reduced to 56 × 57 × 2. This resultant output was fed as an input for CONV2 with kernel size 3 × 3 and stride set at 1 and obtained the output dimension was 54 × 55 × 4.

Similarly, one more convolution (CONV3) and Max Pooling (PL3) was applied as an alternative and the output dimension matrix was 12 × 12 × 8 as summarized in Table 1. We have used the "flatten layer" to reshape the (12 × 12 ×8) dimensional vector into one-dimensional vector size of 1152. It acts as a neural network which learns the features from all the combination of features for classification purpose. Next, the Softmax Activation function was applied then the resultant output was fed as input for the final output layer for classification purposes for predicting user's interest. Fig. 2 illustrates the architecture of the user's interest prediction using MLCNN. We have applied the same model for all the fifteen labels, namely Travel, Technology, Real Estate, Finance, Science, Entertainment, Health, Sports, Religion, Vehicle, Education, Business, Politics, Environment and Lifestyle to predict users' diversified interest with respect to above-mentioned labels. The model has been developed from scratch and not used any transfer learning technique.

Table 1 — CNN architecture hyperparameters

Layer	Type	Output	Size of theFilters	Stride	Value
I	Input	115 × 116 × 1	—	—	—
CONV1	Convolution Layer	113 × 114 × 2	3 × 3	1	—
PL1	Maxpooling	56 × 57 × 2	2 × 2	2	—
CONV2	Convolution Layer	54 × 55 × 4	3 × 3	1	—
PL2	Maxpooling	27 × 27 × 4	2 × 2	2	—
CONV3	Convolution Layer	25 × 25 × 8	3 × 3	1	—
PL3	Maxpooling	12 × 12 × 8	2 × 2	2	—
D1	Dense	—	—	—	—
O	Output	2	—	—	—
Learning rate	—	—	—	—	0.01
Batch size	—	—	—	—	64
Optimizer	—	—	—	—	Momentum
Drop out	—	—	—	—	0.5

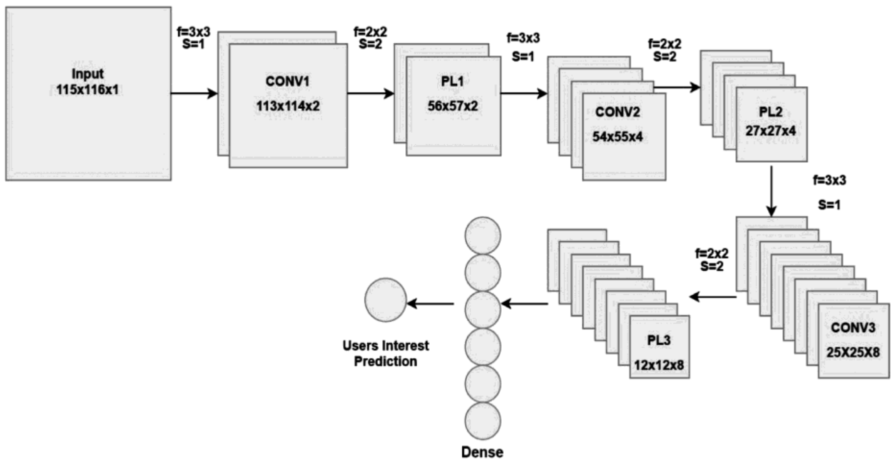

Fig. 2 — Architecture of user's interest prediction using proposed approach (MLCNN

Domain Specific Popularity

News articles and real-world events are spread and talked about by the general population in social networking sites like Facebook and the Twitter. Through this open platform discussion, most prominent and vogue news articles can be distinguished. So, the proposed system helped to determine of the most popular news articles for all the fifteen labels by harnessing social media feeds

The following sections discuss that how to fetch the label wise popular and trending news articles from above mentioned social media alongside breaking news articles from RSS feeds for effective recommendation.

Domain Specific Popularity of Facebook

The numerous news sites have generated the news articles. It was shared and posted by Facebook users on their respective Facebook walls and liked by them. So, the most popular news articles on Facebook can be determined through the maximum number of shares and likes count. The proposed system has helped to discover that popular or trending news articles with the aid of Social Media Monitoring (SMM) tool.

This tool provides domain (label) wise popular news articles in structured manner without any bias.

Each domain labels multiple sub-domains. For e.g. Sports relevant labels such as baseball, cricket, football, tennis, table tennis, etc. are grouped into the sports label. The same thing was applied to the rest of the labels. To work with the tool, lot of information is to be provided to form a query. Once the query has framed, we fetched the popular news articles for last 3 days to till the minute which is having greater number of share and like count. This process has repeated for all the 15 labels. In addition to that, the overall trending news articles were identified with the labels irrespective of user's interest labels including the maximum number of total count (shares + likes) for the recommendation process. This is because that sometimes people were more inclined towards current trends irrespective of interest such as world cup season, Covid 19 pandemic, election time, etc. For this purpose, the trending news articles were also determined for the recommendation process. But before recommending, this overall trending news articles labels were checked with users interesting label. In case, the same label was present in the user interest then trending news articles were removed from the recommendation process to avoid redundancy.

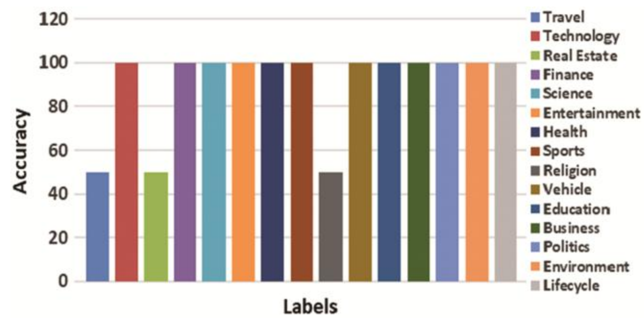

Fig. 3 — Domain specific popularity of Facebook

The performance of the domain specific popularity of Facebook with respect to labels evaluated as shown in Fig. 3. To evaluate this performance, we retrieved two news articles with a higher share count from every label and the retrieved news articles were checked for their relation to the respective labels by using a news classifier. Hence, the accuracy attained was 100%.

Domain Specific Popularity of Twitter

A Twitter crawling engine was constructed for the retrieval of (last 3 days to till the minute) two top most popular tweets (most favourite) and corresponding news articles for all the fifteen news labels related hashtag using Twitter API. Every label contains numerous hashtags.

Therefore, it was required to find all the correlated hashtag for each and every label. So, the related hashtags for a single label were identified using a hashtag search engine tool.

Then tweet counts to every hashtag from the past three days were obtained till the last minute and retrieved the most popular hashtag having the maximum number of tweets excluding re-tweets. Considering those hashtag, the most popular hashtags were determined with the aid of greater number of hashtags. Further, corresponding news articles (text, URL) were retrieved. The same procedure was used for all the other labels. In addition to that, overall trending hashtags were also determined with labels along with maximum number of tweets for the recommendation process irrespective of users interesting labels. But before recommending, this overall trending hashtag labels were checked with users interesting label. In case the same label was present in the user interest then trending news articles were removed for the recommendation process to avoid redundancy. The performance of retrieved label specific news articles on Twitter was evaluated using accuracy as shown in Fig. 4. This evaluation was done similar to Facebook domain specific popularity

Fetching of Domain Specific breaking news articles

The RSS feeds producing the news articles was acquired from numerous agencies. We have collected it for all the 15 labels. The news articles time stamps were checked for each label. The news article that contains with latest time stamp is retrieved for effective recommendation for every label. Fig. 5 illustrates the performance of fetching the domain (label) wise breaking news articles with the corresponding label.

News Articles Recommendation:

MLCNN was applied for the prediction in all the fifteen labels. It has been observed that users interests varied, it may contains more than one label. Based on the user's interest labels, the following are recommended

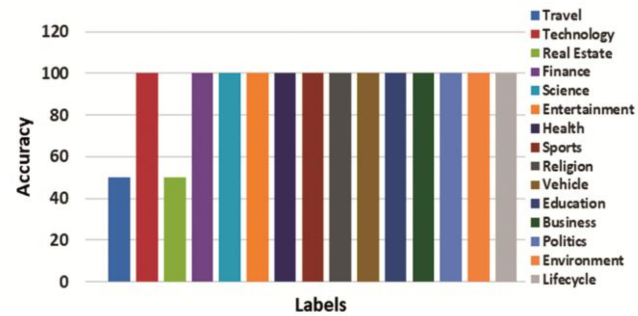

Fig. 4 — Domain specific popularity of twitter

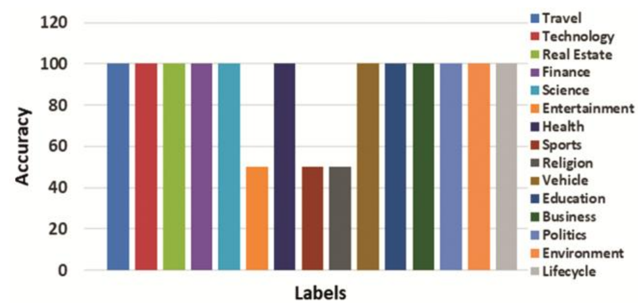

Fig. 5 — Fetching of domain specific breaking news article

- Two fresh news articles (latest time stamp) along with the date, time and label, title and description are retrieved from news feeds.
- Two most popular and trending news articles from Facebook and Twitter validated in IFCN.

Experimental Results

Users Interest Prediction

The experiments were conducted on Yahoo! A4 dataset[35] for measuring the performance of novel CNN architecture designed for predicting users' interest in multi-label domains. This approach was implemented using the deep learning framework Keras with Tensor flow backend on Windows 10 with NVIDIA GEFORCE GT 730 GPU and 16GB RAM. This novel architecture was trained with hyper parameters as mentioned in Table 1 along with 300 epochs per label. The proposed model stops learning by using an early stopping mechanism.

In this mechanism, whenever the model performance reached optimum (maximum) accuracy at some point on the validation set and then turned to become worse with further iterations. The proposed model was also trained with various hyper parameters manually. For instance, the experiments were also conducted using 5 convolution layers along with 5 pooling layers along with one dense layer also experimented with filter size 3 × 3, 5 × 5, with the number of filters 8, 16, 32, 64, 120, stride 1 in convolution layer 2. In pooling layer, the learning rate 0.0001, 0.002 etc. were tuned to get the good classification accuracy. It made the training process significantly longer and did not improve the accuracy. Again, the number of layers was changed to 3 convolution layer and 3 pooling layers with one dense layer. Here also again tried with the number of parameters for filter size 3 × 3, 7 × 7 and stride 2 kept in convolution layer and pooling layer, learning rate 0.1, number filters were changed into 128 and 256. Then, the batch sizes were also hypothesized by increasing the number of batch size 128 and 256 with an increasing number of iterations leads to poor accuracy due to over fitting. Not only above hyper parameters, the number of layers also changed along with decrease in filter count together with gradually increases in epochs. Nevertheless, the accuracy was stable most of the time. Next, the experiments were tried by changing the optimizers SGD, GD, SGD with momentum as well to update the weights. Hence, the accuracy was unable to improve. It means that not only the problem with the optimizers, the all-other hyper parameters combinations should be proper that should fit into the dataset. It may be varied depends upon the problem. After several hypotheses, the final architecture was obtained as summarized as mentioned in Table 1. To analyse the efficiency of the proposed MLCNN classification approach, the following metrics were applied namely Precision, Recall, Specificity, F1-score, NPV and Accuracy and compared with the following state of art peer multi label classification techniques such as SVM, Naïve Bayes, and Decision Tree as summarized in Table 2. The overall performance of proposed MLCNN compared with above mentioned techniques merits, demerits with respect to our dataset is summarized in Table 3.

Table 2 — Label wise comparison between MLCNN with state of peer classification techniques in %

Label Id	Label Name	Method	Precision	Recall	F1-Score	NPV	Specificity	Accuracy
1	Travel	**MLCNN**	**78.39**	**80.9**	**79.62**	**80.26**	**77.7**	**79.3**
		SVM	71.09	73.8	72.42	72.76	70	71.89
		Naïve Bayes	63.47	40.5	49.45	56.31	76.7	58.59
		Decision Tree	67.16	67.5	67.16	67.17	66.5	67
2	Technology	**MLCNN**	**78.58**	**65.7**	**71.56**	**70.53**	**82.1**	**73.9**
		SVM	70.96	61.1	65.66	65.84	75	68.05
		Naïve Bayes	58.1	31.9	41.18	53.06	77	54.44
		Decision Tree	60.27	61	60.63	60.52	59.8	60.4
3	Real Estate	**MLCNN**	**75.15**	**75**	**75.07**	**75.04**	**75.2**	**75.1**
		SVM	67.97	69.19	68.58	68.63	67.4	68.3
		Naïve Bayes	61.49	36.1	45.49	54.7	77.4	56.75
		Decision Tree	61.83	62.7	62.26	62.17	61.3	62
4	Finance	**MLCNN**	**78.88**	**79.2**	**79.04**	**79.11**	**78.8**	**79**
		SVM	70.91	81.2	75.71	78.01	66.7	73.95
		Naïve Bayes	62.92	39.2	48.3	55.84	76.9	58.05
		Decision Tree	70.03	64.5	67.15	67.09	72.39	68.45
5	Science	**MLCNN**	**76.65**	**77.5**	**77.07**	**77.24**	**76.4**	**76.95**
		SVM	71.55	65.2	69.62	69.12	77.9	71.55
		Naïve Bayes	57.7	31.2	40.51	52.8	77.2	54.2
		Decision Tree	65.53	63.7	64.6	64.68	66.5	65.1
6	Entertainment	**MLCNN**	**75.62**	**75.1**	**75.36**	**75.27**	**75.8**	**75.44**
		SVM	70.1	65.9	67.93	67.83	71.89	68.89
		Naïve Bayes	63.92	38.8	48.28	56.06	78.1	58.45
		Decision Tree	63.01	66.1	64.51	64.35	61.19	63.65
7	Health	**MLCNN**	**77.15**	**77**	**77.07**	**77.04**	**77.2**	**77.1**
		SVM	67.94	72.7	70.2	70.64	65.7	69.19
		Naïve Bayes	65.52	42	51.18	57.32	77.9	59.95
		Decision Tree	64.08	61.19	62.6	62.87	65.7	63.44

(*Contd*.)

Table 2 — Label wise comparison between MLCNN with state of peer classification techniques in % (*Contd.*)

Label Id	Label Name	Method	Precision	Recall	F1-Score	NPV	Specificity	Accuracy
8	Sports	**MLCNN**	**77.01**	**77.4**	**77.2**	**77.28**	**76.9**	**77.14**
		SVM	74.03	69.3	71.59	71.14	75.7	72.5
		Naïve Bayes	60.7	75.7	67.37	67.72	51	63.49
		Decision Tree	64.63	65.8	65.21	65.17	64	64.9
9	Religion	**MLCNN**	**82.25**	**83.89**	**83.06**	**83.57**	**81.89**	**82.89**
		Naïve Bayes	71.75	53.1	61.03	62.77	79.11	66.1
		SVM	82.06	74.6	78.15	76.71	83.7	79.14
		Decision Tree	71.88	69.3	70.57	70.3	72.89	71.1
10	Vehicle	**MLCNN**	**73.56**	**84.3**	**78.56**	**81.61**	**69.69**	**77**
		SVM	71.19	69.69	70.43	70.32	71.8	70.75
		Naïve Bayes	64.24	70.8	67.36	67.48	60.6	65.7
		Decision Tree	64	63.3	63.65	63.69	64.4	63.84
11	Education	**MLCNN**	**79.06**	**79.7**	**79.38**	**79.53**	**78.9**	**79.3**
		SVM	69.82	76.6	73.05	74.08	66.9	71.75
		Naïve Bayes	63.54	38	47.55	55.77	78.2	58.09
		Decision Tree	65.32	65	65.16	65.17	65.5	65.25
12	Business	**MLCNN**	**83.03**	**82.69**	**82.86**	**82.76**	**83.1**	**82.89**
		SVM	81.18	63.6	74.36	72.81	84.1	76.35
		Naïve Bayes	57.47	80	66.88	67.1	40	60.4
		Decision Tree	73.82	70.8	72.28	71.95	74.9	72.85
13	Politics	**MLCNN**	**77.61**	**72.8**	**75.12**	**74.38**	**79**	**75.9**
		SVM	70.5	73.4	71.92	72.26	69.3	71.35
		Naïve Bayes	59.96	38.5	46.89	54.71	74.3	56.39
		Decision Tree	57.47	80	66.88	67.1	40.8	60.4
14	Environment	**MLCNN**	**76.85**	**75.7**	**76.27**	**76.05**	**77.2**	**76.44**
		SVM	71.69	68.4	70.01	69.78	73	70.7
		Naïve Bayes	65.94	42.8	51.91	57.66	77.9	60.35
		Decision Tree	65.33	65.4	65.36	65.36	65.3	65.35
15	Lifecycle	**MLCNN**	**80.91**	**84.8**	**82.81**	**84.03**	**80**	**82.39**
		SVM	82.94	71	76.5	74.65	85.39	78.2
		Naïve Bayes	59.11	79.8	67.91	68.92	44.8	62.3
		Decision Tree	75.22	74.1	74.65	74.48	75.6	74.85

Table 3 — Comparison of our proposed MLCNN with peer multi label classification techniques

Classification Techniques	Characteristics	Label wise Performance	#MLCP (Accuracy %)	Merits	Demerits
Naïve Bayes	It assumes all the features are conditionally independent. It gives equal weightage for all the features.	It was unable to reach even 60% accuracy in all the labels except the following labels 8, 9, 10, 12, 14 and 15.	59.55%	Convergence Faster	▪ It doesn't perform well for large number of dataset with large number of features
Decision Tree	It transforms the data into tree representation for making decision	It attained above 70 % accuracy in the following labels 15, 12, and 9 labels. Rest of the labels attained above 60 to 70 % accuracy.	65.95%	Less effort only required for data pre-processing.	▪ Tree Size will be larger due to more number of features. ▪ Minor change in the data may provide the decision wrong ▪ Computation Time more
SVM	It iteratively draws the hyperplane to explore the perfect hyperplane with greater margin for classification	It reached around 70% accuracy in all the labels besides 2, 3, 6 and 7	72.17%	Memory efficient Works well for high dimensional spaces	▪ It was unable to learn the hyperplane on nonlinear kernel space under too sparse data. ▪ Not suitable for large dataset

(*Contd.*)

Table 3 — Comparison of our proposed MLCNN with peer multi label classification techniques (*Contd.*)

Classification Techniques	Characteristics	Label wise Performance	#MLCP (Accuracy %)	Merits	Demerits
MLCNN	It consists of multiple layers to perform classification process.	It attained above 75% accuracy in all the labels apart label 2.	78.04%	Automatic features extraction and classification Training time will be more	Manual tuning of hyper parameters.

#MLCP = Multi label classification performance (Accuracy %)

Metrics other than accuracy as represented in Figs 6–10 have performed well. The overall average accuracy of all the labels of MLCNN SVM, Naïve Bayes, and Decision Tree attained 78.04%, 72.17%, 59.55% and 65.95% respectively as represented in Fig. 11. These experimental results undoubtedly indicated that our proposed approach MLCNN attained good classification accuracy for all the 15 labels in all the aspects as compared to all the state of art classification techniques as summarized in Table 2 and 3.

Note

This architecture has been developed from scratch and has not used any predefined architectures and its weights. Similarly, the dataset was also pre-processed from scratch. The architecture uses a binary relevance mechanism and is trained by various hyper parameters based on several kinds of literature manually also implemented using caviar approach.

Recommendation Accuracy

Considering the accuracy of the recommendation process, we have taken ten users randomly for recommending fresh and popular news articles based on their interest labels. The recommended news articles labels were determined using a news classifier. Next, the recommendation efficiency was evaluated according to user's interest labels as well as retrieved news article labels. The overall recommendation performance of our proposed system is depicted in Fig. 12.

The performance of proposed HYPNRS compared with peer HYPNRS popularity recommendation is summarized in Table 4. The peer HYPNRS recommended the most popular news articles from Twitter excluding Facebook. So, the performance was evaluated based on incorporating the most popular news articles from Twitter with respect to users interests labels for proposed system as well as peer HYPNRS. This was monitored during the period of 10 days (Overall average 10 days recommendation performance).

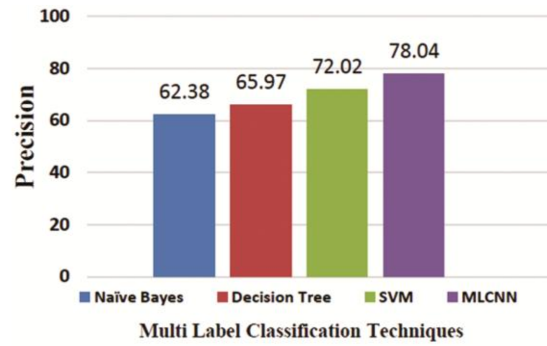

Fig. 6 — Overall average precision for 15 labels

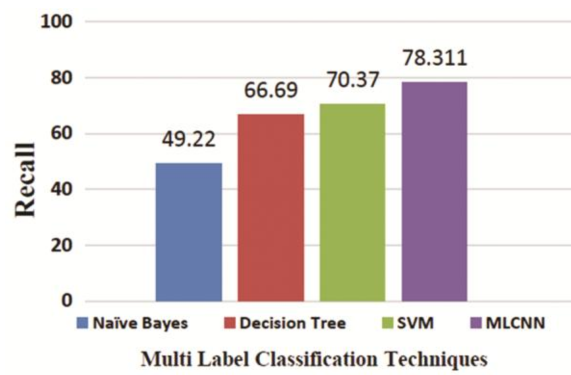

Fig. 7 — Overall average recall for 15 labels

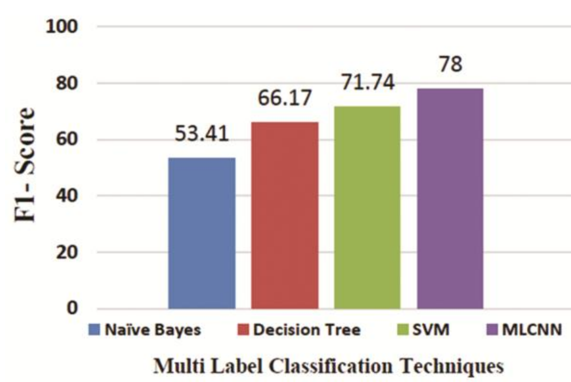

Fig. 8 — Overall average F1-score for 15 labels

The peer HYPNRS popularity recommendation from Twitter is excluding Facebook. They did not validate the reliability of the news articles. But we

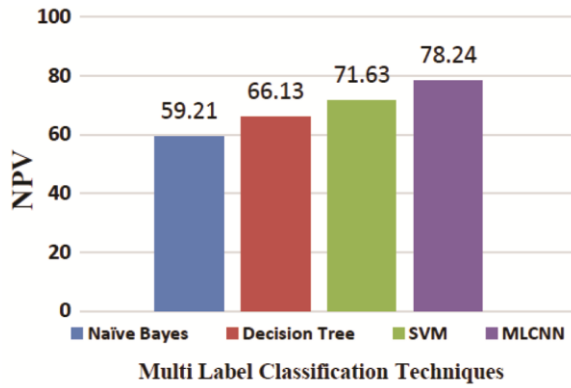

Fig. 9 — Overall average NPV for 15 Labels

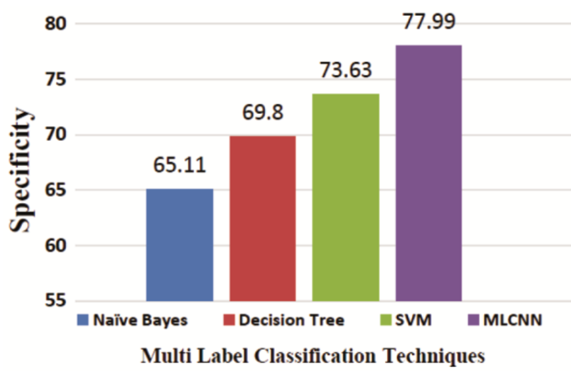

Fig. 10 — Overall average specificity for 15 Labels

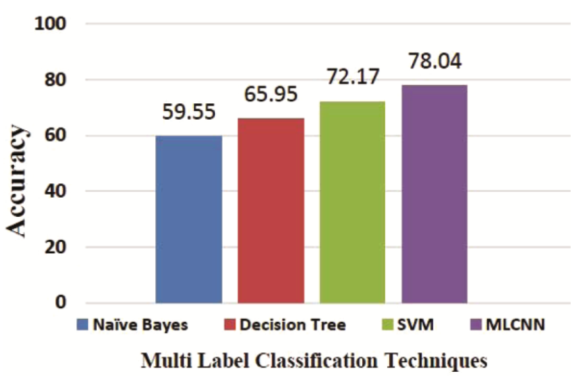

Fig. 11 — Overall average accuracy for 15 Labels

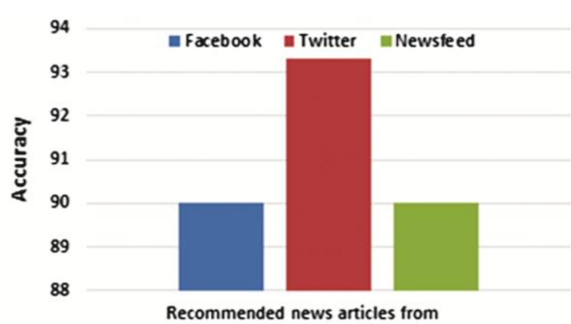

Fig. 12 — News recommendation accuracy

Table 4 — Performance comparison with HYPNRS (proposed system popularity) vs peer HYPNRS popularity recommendation

Proposed System Popularity Recommendation Evaluation (Accuracy) based on Twitter for 15 labels	Peer HYPNRS Popularity Recommendation[31] Evaluation (Accuracy) based on Twitter for 15 labels
93.3%	87%

recommended personalized based popularity recommendations from Twitter and Facebook as well. Before recommending popular news articles the reliability of the news articles also validated in IFCN.

Conclusions

The novel CNN architecture was developed for the Yahoo! dataset with multi labels (15 labels) having 13,346 features per user for the context of users' interest classification in this proposed work. For developing architecture, this proposed work did not use any transfer learning techniques and the dataset was not used by anyone for predicting the user's interest. Hence, the architecture was developed from scratch, did not use any predefined trained model and its weights, similarly dataset was also pre-processed from scratch. The developed architecture uses binary relevance mechanism and trained by various hyper parameters based on several literatures manually.

Once the architecture developed for one label, it was applied to the rest of the labels as well. Thus, the users' interest predicted for 15 labels using MLCNN. The users' interest varied for every label. Some of the users have shown their interest in more than 10 labels as well. Based on users label specific interests, the most popular and trending news articles were identified and recommended from social networking sites Twitter and Facebook using a social media monitoring and hashtag search engine tool. Redundancy was also removed and they were also validated in IFCN. Finally, they were integrated with breaking news articles from news aggregators on the basis of user's interest for recommendation.

The performance of the proposed users' interest prediction approach was improved from the accuracy of 5.87%, 18.49% and 12.09% as compared to state of art peer multi label classification techniques namely SVM, Naïve Bayes and Decision Tree. Based on predicted users interest labels, the overall recommendation efficiency reached 93.3%, 90%, and 90% respectively.

This proposed work can be extended by tuning the hyper parameters in MLCNN automatically by using optimization techniques to get the optimized CNN architecture for all the labels separately to enhance the classification accuracy for user's interest prediction purposes.

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