MOWIR: Metadata Centered Ontology Controlled Web Image Recommendation Scheme for Botanical and Horticultural Domains

Gerard Deepak[1]Pavan Satya Krishna[2],Unnam Lasya B[2], Kadavath Deekshitha[2],Ashu Aravind[2], Naga Yethindra Y[3], Santhanavijayan A[4]

[1,2]Department of Computer Science and Engineering

[1]Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India

[2]National Institute of Technology, India

[3]Kings College London, United Kingdom

Abstract

Web image retrieval is semantically inclined, and knowledge driven is the need of the hour due to increase in the multimedia contents on the world wide web. In this paper, web image retrieval framework, which is semantically driven knowledge centric Web 3.0 complaint has been proposed. The proposed framework MOWIRframework is a Metadata Centered Ontology Controlled Web Image Recommendation Scheme for Botanical and Horticultural Domains. In this framework Ontology Modeling and Generation is coupled with differential Classification using the LSTM and Logistic Regression classifiers at varied levels. The Ontology Alignment tasks ensures a fair amount of auxiliary knowledge is anchored with a high degree of relevance to the domain and the Metadata Generation exponentially increases the knowledge from global Web to the localized framework for recommendation reducing the cognitive knowledge gap. This framework strategically integrates a feature-controlled Machine Learning Classifier and a Deep Learning Classifier at two distinct instances to enhance variational diversity in learning. An array of semantic similarity computation measures with a differential threshold and deviance criterion are employed in the framework for increasing the strength of relevance computation. The proposed MOWIR achieves an overall Precision of 93.11% with an average F-Measure is 95.24% with a very low False Discovery Rate (FDR) of 0.07 which outperforms the baseline approaches.

Keywords: Semantically driven, LSTM, Logistic Regression, Text classification.

1 INTRODUCTION

Without a doubt, data is incredibly important and only becoming more so as Digital Transformation dominates the Infotainment Technologies . Its sheer volume increase is prompting information technologists to be apprehensive, as they are responsible for storing, preserving, and managing the data. Withnearly 5 billion active users, the internet is accessible to 60% of the world's population. They are mostly mobile and utilize social media. On our little globe, there is a lot of data per person, by any measure. More people are gaining access to the internet, mobile networks every day. IT and entertainment companies are finding new ways to consume more bandwidth and storage with improved services such as entertainment and news, higher definition digital content,5G network and many more. It is elementary for the average user to create and share all types of multimedia content because of the growing prevalence of Internet-friendly, low-cost commodity cameras (such as mobile phones, security cameras, etc.) and the proliferation of social networks (such as Webchat, Flicker, Facebook, YouTube, Twitter, etc.).

The W3C's concept of the Web of linked data is known as the "Semantic Web." Semantic Web technologies make it possible for users to develop vocabularies, implement data handling rules, and create data stores on the Web. The semantic Web is knowledge-centric, whereas individual instances on the Web are informative. In the semantic web density of data is extremely high. When data density is large, it is difficult to search for high dense data such as semantic Web. Since the Web is transforming into semantic Web the new strategies should be semantically driven knowledge-centric modules.Information is often best communicated through visual means. The amount of digital image data is rapidly increasing due to the rapid development of computer technology. There will always be a need for efficient methods to assist users in searching for and retrieving visual information A computer system known as an image retrieval system is used to browse, search for, and retrieve images from a sizable database of digital images.

Motivation: There is a need for appropriate, semantically oriented methods for recommending images on the web. Due to a lack of semantically oriented strategies and the fact that current strategies do not support the future semantic models that will propel Web 3.0, we opt for image retrieval.

Contribution: A MOWIR (Metadata Centered Ontology Controlled Web Image Recommendation Scheme for Botanical and Horticultural Domains), which is semantically driven and knowledge centric has been proposed. The dataset is fed to a Logistic Regression classifier which is a feature controlled machine learning classifier and the framework generates metadata as Auxiliary Knowledge and is classified using the Long Short-Term Memory deep learning classifier at a differential scale The proposed MOWIR framework encompasses Ontology Alignment at different levels for auxiliary knowledge induction and an array of semantic similarity schemes with differential thresholds has been instilled into the mode. Performance metrices such as Recall, Precision, F measure and Accuracy are increased and the False Discovery Rate is reduced when compared to the baseline models.

2 RELATED WORKS

Khalid Hameed Zaboon et al., [1] have proposed a study that suggests an effective and scalable online learning framework as well as a novel classroom learning system for online Multi-modal Dimensional Learning (OMDML). This study suggests a low-rank OMDML calculation, which lowers the computational cost while keeping extremely competitive or significantly greater learning accuracy. J Faritha Banu et al., [2] have proposed the research on content-based picture retrieval has advanced thanks to studies on image indexing and retrieval principles (CBIR). This approach uses texture and texture as visual cues to characterize the content of an image. To evaluate the contents, an ontology model is created. Hui Wu et al., [3] have recommended focusing on numerous discriminative local patterns in a picture at the same time. Numerous tests on the Revisited Paris and Oxford datasets show that the suggested strategy works better than the most recent methods. Shiv Ram Dubey et al., [4] have proposed a framework for content-based image retrieval by comparing a query image with similar images from a huge dataset and gives a thorough analysis of the progress made in the last ten years in content-based picture retrieval using deep learning.

Chenggang Yan et al., [5] proposed this method is the CIFAR-10, MIS-COCO and NUS-WIDE datasets were carefully tested, and the findings demonstrate that our method surpasses the most recent single-view and multi-view hashing techniques. Huimin Lu et al., [6[proposed the purpose of hashing algorithms for successful image retrieval is to provide Learning hash functions that map related images to semantically related binary codes in the Hamming space while preserving similarity. The hand-crafted features used in classic hashing algorithms typically represent image. Le Wu et al. [7] proposed the hierarchical attention network model that learns for attending to information differently imbibing word embeddings through strategic deep learning techniques. The deep learning models are designed separately for varied types of data. Lastly, thorough experimental outcomes conducted on datasets that are universally available on the Web. unequivocally depicted the superiority. Meng Jian et al., [8] proposed social curation networks' that contains bipartite graph for facilitating image recommendations using information content. For inferencing the correlation of users and images for recommendations, bipartite graphs leverage sparse user-image interactions. Experiments demonstrate the efficacy of the formulated bipartite graph driven recommendation framework. Guibing Guo et al., [9] proposed to better recommend a solution, use the Visual Semantic Model (VSM). To be more precise, integration feature embeddings with objects that are fine-tuned from the images whose vary depending on the user.

Changqin Huang et al., [10]have proposed retrieval of vast-scale Semantic Web images utilizing dual model techniques with deep learning methods. Convolutional Neural Networks (CNNs) are used to implement and propose Multi-concept Retrieval using dual modal Deep Learning with concept heterogeneity technique has been proposed, an advanced retrieval system that can efficiently extract semantic correlations between a visual image and its free contextual tags. Huanyu Li et al., [11] proposed a Bagging model with hashing h based on weights integrated with web usage structural information is a new technique for retrieving web images. The proposed hashing method's online web use case paradigm scenario is the "search by image." BWLH is provided to explain how the suggested method can be applied in a web-based setting. In [16-22] several Ontological Models in support of the proposed framework have been depicted.

3 PROPOSED SYSTEM ARCHITECTURE

Fig. 1 depicts the proposed architecture of Web Image Recommendation Model for Botanical and Horticulture as a domain of choice. The Web Usage Data from the users is subjected to along with the query that is input. Pre-processing. This pre-processing includes tokenization, lemmatization and stop word removal and Named Entity Recognition (NER). The preprocessed query words and web usage data furnishes the individual query terms and tokenized terms from the Web Usage Data. The Incidence between Web Usage Data that constitutes historical visits of the user as well as the current user clicks has been considered as the initial terms which drive the entire process of recommendation. The Incidences indicate a higher order of preferential information content. The metadata generation is carried out to increase the quantity of auxiliary knowledge using the Open Calais tool. The need for metadata generation is to ensure the terms taken from the web using data and the query terms become more Informative. The metadata is exponentially large, it is classified using Long Short-Term Memory (LSTM) Classifier. The LSTM is a Deep Learning classifier where the features are automatically discovered by LSTM. The top 60% of the classified instance that emerge out of each class is discovered and retained to handle the large quantity of metadata. The output of Query Terms and the Web Usage Data Terms are subject to Ontology Alignment with the Domain Ontology and the Scientific Taxonomy. The Domain Ontology is pertaining to the Botanical and Horticultural domain which is extracted and formulated using two different tools namely the Web Protégé for static ontology modeling and OntoCollab for dynamic ontology synthesis.

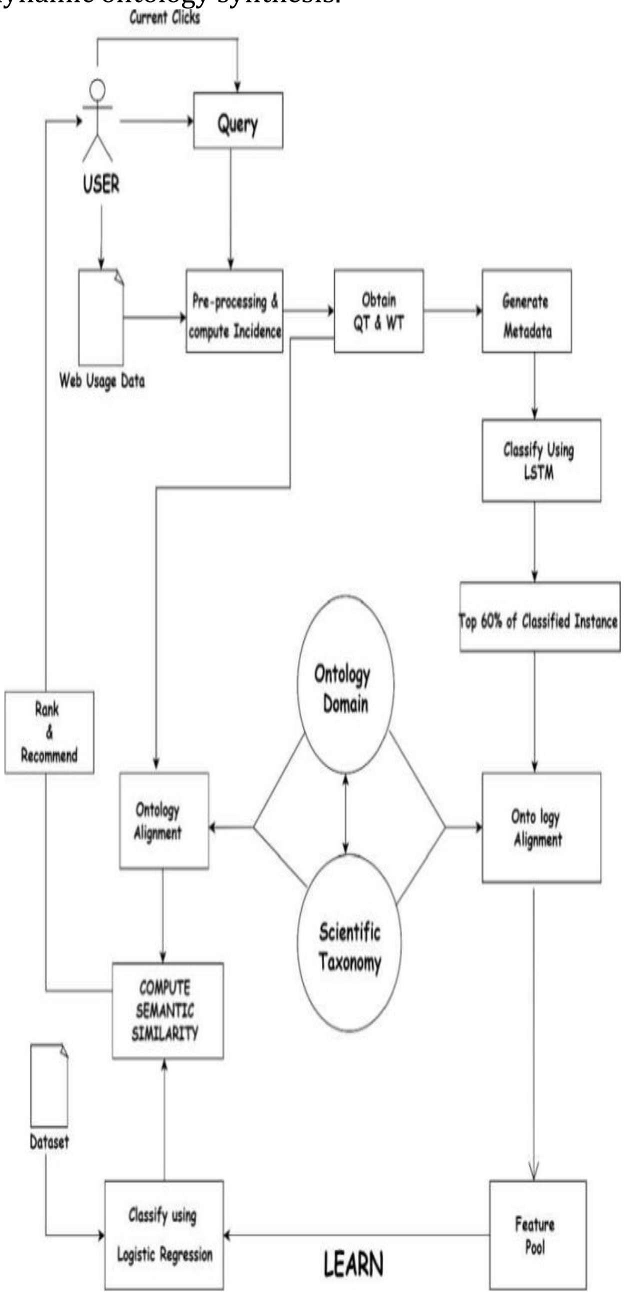

Fig.1. Proposed System Architecture of the MOWIR Framework

To model the static domain Ontology, Botany and Horticulture Domains focus on information modeling of classes of flowers, fruits, vegetables, herbs, plants, fungi, algae. Scientific taxonomy is subjected to modeling by terms present in the dataset which was partially modeled using Web Protégé and partially generated using Stardog as

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individual tools. Both the domain ontology and scientific taxonomy are subject to ontology alignment using the Lin Similarity Measure with a threshold of 0.5 with the top 60% of the classified instances by computing the PMI similarity with the threshold of step deviance of 0.35 and two distinct levels. The feature pool is yielded and the features in feature pool are used for training the Logistic Regression classifier which is used to classify the dataset. The reason for employing the Logistic Regression Classifier is due to the fact it is a Machine Learning Classifier and has a mechanism where the features be controlled because it works on the principle of uncontrolled feature selection. The output of the classified dataset which is categorical in nature is further subject to semantic similarity computation and the classes yielded by the Logistic Regression Classifier are further subject to Semantic Similarity is computation using two measures namely the SemantoSim Measure which is set to a threshold of 0.75 and Morisita Index which is set to be step deviance of 0.25. The categories and labels in the dataset and the classes along with ontology taken by enriching the QT & WT are used as participating entities for semantic similarity computation.Finally, the images containing the labels as terms are ranked. Along with the Images the labels are also ranked in ascending order of SemantoSim measure of the corresponding images are furnished by the user. The user is furnished labels with images. If the user is satisfied the recommendation halts else the current user clicks recorded are fed as query word and this process continues until there are no further user clicks recorded.

Using the supervised learning classification procedure notorious as logistic regression, the likelihood of a target adaptable is predicted. There would only be two classes because the intent conversely defenseless adaptable is bifurcate in nature. Machine learning has adapted the categorization method known as logistic regression from statistics. A demographic technique such as examining ASCII file one or more in reliant adaptable affect an outcome is called logistic regression.Finding the model that best captures the relationship between the dependent and independent variables is the goal of utilizing logistic regression. In logistic regression, the arched activity is employed to translate predicted values into anticipation. Any appraise can be transformed into a value between 0 and 1 with this function. This function has exactly one inflection point and a non-negative derivative at each point.

A counterfeit neural network disclosed long short-term memory is utilized in deep learning and artificial intelligence. Because LSTM is a deep learning classifier, it automatically learns the features because it supports feature selection. With LSTMs, unlike the hidden Markov model, there is no obligation to preserve a finite number of states from the beginning (HMM (Hidden Markov Model)) Learning rates, accrual, affair biases and learning rates are only a few of the criterion furnished by LSTMs. The LSTM contains a capability that allows it to memorize the data sequence. It operates by removing information that is no longer in use.LSTMs can selectively remember or forget information. The connection between LSTM and conveyor belts is a key characteristic. They are used in industries to transport items around for various operations. This method is used by LSTMs to transfer information around; because of this trait, LSTMs do not manipulate the complete information but modify it slightly, allowing them to selectively forget and remember items. It is because of the meta data properties that they are very quickly learned and classified. The backpropagation's cant-based update and the LSTM's cell-state antique have a lot in common. A measure of mutual information is how much knowledge one stochastic variable has farther stochastic variable. It is the abatement in one stochastic variable's unpredictability because of the understanding of the other.

$$I(X;Y) = \sum_{x,y} p(x,y)\, ln \frac{p(x,y)}{p(x)p(y)} \quad (1)$$

Equation (1) depicts from Lin similarity The Mutual Information is given by Equation (3). When X and Y are independent, there is no information overlap between them because p(x) p(y) = p. (x, y) I (X; Y) = H(Y) when X determines Y, where H(Y) is the decay of, or famine of information about, Y, and defined as:

$$H(Y) = -\sum_{y} p(y) \ln p(y) \quad (2)$$

I (X; Y) reaches its optimum of H(X) = H(Y) = H (X, Y), where H (X, Y) is the joint decay of X and Y, which we obtain by substituting the marginal distribution in (2) with the joint distribution p. (x, y).

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \quad (3)$$

$$I(X:Y) = E_{p(X,Y)}\,[i(X,Y)] \quad (4)$$

$$I(X;Y) = \sum_{x,y} p(x,y) i(x,y) \quad (5)$$

$$i(x,y) = \ln \frac{p(x,y)}{p(x)p(y)} \quad (6)$$

Equations (2),(3),(4),(5),(6) indicates PMI measure and Cosine similarity Measures. PMI measure is given by Equation (7). Pointwise Mutual Information (PMI) is a measure of the real likelihood of a certain pair of events occurring together (p (x, y)) differs from what we would anticipate it to be given the probabilities of the individual events and the independence assumption p(x)p (y). Note that although PMI may be either positive or negative, MI is the predicted outcome over all joint events.

$$pmi(x,y) = log\frac{p(x,y)}{p(x)p(y)} (7)$$

Even if PMI can be either positive or negative, its anticipated result over all occurrences is always nonnegative. Morisita's overlap index is a statistical measure of individual dispersion in a population named by Masaaki Morisita. It is used to compare sample overlap (Morisita 1959). This method is positioned on the notion that increasing the sample size will improve variety since different habitats will be included.

$$C_D = \frac{2\sum_{i=1}^{S} xiyi}{(D_x+D_y)XY} (8)$$

Equation (8) depictstheMorisita Overlap Index.The count of category I appear in totality of X from a single sample is xi. The count of category I is depicted in the totality of Y from alternate sample is indicated by yi. The Simpson's basis values for x and y samples are Dx and Dy, respectively. The number of distinct categories is denoted by the letter S.CD = 0 if the two samples have no category overlap, and CD = 1 if the category are present in equal quantities in twain samples. Lin Similarity Measures are Node-based Semantic Similarity Measures that are based on the detailed willing of the minimal prevailing subsume. This is how it is explained:

$$\frac{2 \times Resniksimilarity(c1,c2)}{IC_{(c1)}+IC_{(c2)}} (9)$$

$$SemantoSim(x,y) = \frac{pmi(x,y)+pCx,y)\,[\log p(x,y)]}{[p(x).p(y)]+[\log p(y,x)]} (10)$$

The SemantoSim measure, a normalized semantic measure derived from the PMI measure is Semantic similarity metric.The SemantoSim depicted in Equation (10) determines how semantically connected two phrases are (x, y). Equation is used to calculate pmi(x, y) (1). The probability of the phrase x occurring with y is given equation p (x, y). The chance of the phrase y occurring with x is p (x, y). The probability of the terms x and y being present are denoted by p(x) and p(y)

4 IMPLEMENTATION

The proposed framework was implemented in python 3.10.2 using google Collaboratory as the IDE on an i7 intel core processor with 3.8GHz of clock speed on a 32GB ram and the python natural language tool kit (NLTK) library was used for conducting the pre-processing tasks. Ontologies were automatically generated using onto collab and mannerly modelled using the protege 5.5. Experimentations were conducted for datasets ranging from agriculture and horticulture domains and the datasets include the botanical and horticulture domains which include 1. gbif.org Herbarium specimen's dataset from the gbif.org 2. India area: horticulture crops: vegetables: Assam data set from CEICdata.com. 3. Plant_ leaves dataset from tensorflow.org and 4. Leave data base of native plants of Jammu & Kashmir dataset.

Experimentations were conducted for these datasets and most of the datasets have labelled and ungraded images but some of them will have only the data and statistics and terminologies , in those datasets the images were absent and data, statistics and terminologies were taken and these data was using the web crawler they may use as labels to crawl the image contents from the world wide web by using automatic crawlers and also manually querying them by means of agent and through the wing and as well as google image dataset search engine and yield the images. These images were annotated and put in linked to the dataset. Ultimately the dataset consists of the terms, categories as well as the images and all the four datasets were fused to get that to take the experimentations for botanical and horticulture domains. The algorithm is presented below for this approach.

Input: User Query Qu, Web usage W, Domain ontology Do, Scientific taxonomy St, Data set Ds

Output: Ranked and recommended Image set Is in the increasing order of their semantic similarity.

Begin

Step 1: Preprocessing of Qu, W is done using precession, recall, accuracy, F measure and are broken into tokens by a) tokenization, b) lemmatization, c) stop word, d) removal, e) named entity recognition.

Step 2: For each Qt and Wt generate metadata using web protege, ontocollab, stardog tools.

Step 3: Classify the metadata using LSTM and yield the classified instances Ci for top 60% of the classified Ci

For each Is align:

Qw < User query from web usage data

End For

Step 4: Qwm < Metadata generated for Qw terms using LSTM, Logistic Regression classifiers

Step 5: Model = LogisticClassifier.fit(Individual user query words Qu)

Model.transform(Metadata Qwm)

Qt = Select top 60% of classified Instances

Step 6: Model = LogisticClassifier.fit(Individual user web usage W)

Model.transform(Metadata Wtm)

Wt = Select top 60% of Classified Instances

Step 7: Model = LogisticClassifier.fit(Individual user Dataset Ds)

Model.transform (Dataset)

Ds = Classified Dataset Instances

Step 8: For each a in Qt, b in Wt and c in Ds:

Semantosim(a,b,c) [0.75] > Thr. [0.35] from Domain ontology and Scientific taxonomy

Step 9: Ranked and recommended Image set is in increasing order of their semantic similarity

End

5 PERFORMANCE EVALUATION AND RESULTS

The performance of the proposed MOWIR which is a Metadata Centered Ontology Controlled Web Image Recommendation Framework is semantically driven and knowledge centric, its performance is evaluated using Precision, Recall, Accuracy, F measure, Percentages and FDR as potential methods. FDR quantifies the count of false positives apprehended by the module/ frameworks whereas the other metrics quantify the relevance of the results.To evaluate the performance of MOWIR; HAIR. CBCIR, VSIR & Collaborative Filtering+ Cosine Similarity were used as baseline models. To enumerate the performance of the proposed model inherent methods like Precision, Recall, accuracy, F measure & FDR were used in the standard formulations.

Table 1. Comparison of Performance between proposed MOWIR and other models

Model	Average Precision %	Average Recall %	Average Accuracy %	Average F-Measure %	FDR
HAIR [1]	87.33	90.21	88.77	88.74	0.13
CBCIR [2]	88.63	92.22	90.42	90.39	0.12
VSIR [3]	90.12	93.63	91.87	91.84	0.10
Collaborative Filtering+ Cosine Similarity	88.66	90.63	89.64	89.63	0.12
Proposed MOWIR	**93.11**	**9746**	**95.28**	**95.24**	**0.07**

From Table 1 it is evident that the MOWIR yields overall average of highest precision of 93.11%, with average recall of 97.46%, having average accuracy of 95.28%, 95.24% average F measure with a lowest FDR of 0.07. It is also clear that baseline model HAIR [1] yields an overall average of 87.33% precision, 90.21 % recall, 88.77% accuracy, 88.74% F measure & FDR of 0.13. So, CBCIR [2] yields an average of 88.63% precision, 92.22% recall, 90.42% accuracy, 90.39% F measure & FDR of 0.12. VSIR [3] yields an average of 90.12% precision, 93.63% recall, 91.87% accuracy, 91.84% F measure & FDR of 0.10. Collaborative Filtering + Cosine Similarity yields an overall average of 88.66% precision, 90.63% recall, 89.64% accuracy, 89.63% F measure & FDR of 0.12.The performance of the MOWIR is better because of several reasons. It is a domain centric knowledge driven web image recommendation framework which is both metadata driven and ontology center. The metadata generated is in exponentially large volumes which is classified by a deep learning classifier named as LSTM, further enriched by the Domain ontology and Scientific taxonomy classified by a machine learning classifier named Logistic Regression apart from these semantic similarities computed using the SemantoSim measure.

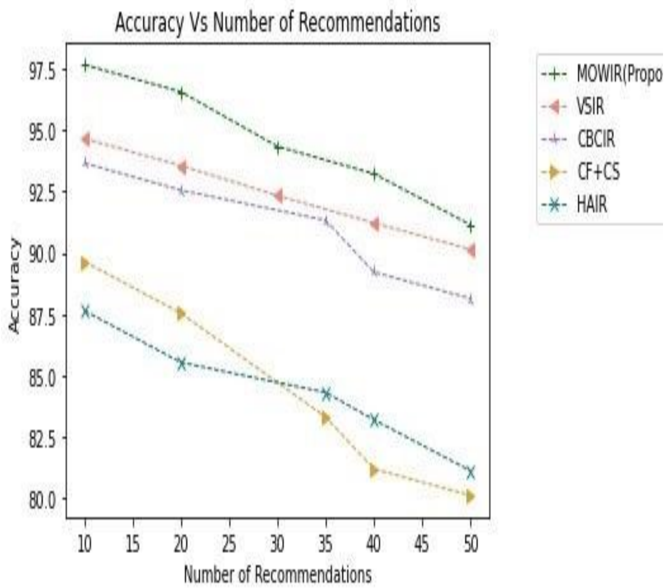

Fig.2. Accuracy Vs No. of Recommendations Distribution Curve

The Accuracy Vs No. of Recommendation Distribution Curve is depicted in Fig.2. In HAIR [1], strong relevance computation mechanism is absent. This model does not perform well as predefined weights are used and because of lack of auxiliary knowledge the cognitive gap is quite large. The CBCIR [2] is not good as MOWIR framework because auxiliary knowledge is not taken into consideration with content and text-based co-relation in which the semantic similarity measures schemes are strong; graphs relevance computation mechanism is also not strong. VSIR [3] also does not perform well because visual semantic similarities computed between the content of the image, and it does not use auxiliary knowledge which causes large semantic gap between external and localized framework knowledge. The CF+CS does not perform well because it does not take into the consideration of the relevance of the query and that is why this model also Lags.The uppermost position is occupied by MOWIR, the next position is occupied by VSIR followed by CBCIR, fourth hierarchy is CF+CS and last position is occupied by HAIR. The proposed MOWIR model hybridizes two different classifiers including meta data, taxonomy, domain ontology and has a strong semantic similarity computation scheme mechanism. This model performs much better than the other baseline models.

6 CONCLUSIONS

Due to the Drastic Increase in image content in the World Wide Web and model meta data centric framework in web image retrieval has been proposed. The meta data centric framework for web image retrieval incorporates the metadata generated is in exponentially large volumes, further enriched by the Domain ontology and Scientific taxonomy apart from these semantic similarities computed using the semantosim measure which have been made use of then deep learning classifier LSTM, machine learning classifier Logistic Regression have been made use of. It is query driven and auxiliary knowledge is added using the relevance computation mechanism is done by using computing Semantic similarities with differential thresholds using semantosim measure, domain ontology and scientific taxonomy measures an overall average of highest 93.11% precision, 97.46% average recall, 95.28% average accuracy, 95.24% average F measure with a lowest FDR of 0.07 are achieved which are better than baseline models.

REFERENCES

Zaboon, K. H. (2022). Determination of multi-modal dimension metric learning with application to web image retrieval. Iraqi Journal of Intelligent Computing and Informatics (IJICI), 1(1), 34-40

Banu, J. F., Muneeshwari, P., Raja, K., Suresh, S., Latchoumi, T. P., & Deepan, S. (2022, January). Ontology Based Image Retrieval by Utilising Model Annotations and Content. In 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 300-305). IEEE.

Wu, H., Wang, M., Zhou, W., & Li, H. (2021). A vast database of digital photographs is browsed, searched for, and retrieved using a computer system known as an image retrieval system. International Conference on Computer Vision, Proceedings, IEEE/CVF (pp. 11416-11425)

Dubey, S. R. (2021). A decade survey of content-based image retrieval using deep learning. IEEE Transactions on Circuits and Systems for Video Technology, 32(5), 2687-2704.

C. Yan, B. Gong, Y. Wei and Y. Gao, "Deep Multi View Enhancement Hashing for Image Retrieval," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 4, pp. 1445-1451, (1 April 2021)

H. Lu, M. Zhang, X. Xu, Y. Li and H. T. Shen, "Deep Fuzzy Hashing Network for Efficient Image Retrieval," in IEEE Transactions on Fuzzy Systems, vol. 29, no. 1, pp. 166-176, (Jan. 2021)

L. Wu, L. Chen, R. Hong, Y. Fu, X. Xie and M. Wang, "A Hierarchical Attention Model for Social Contextual Image Recommendation," in IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 10, pp. 1854-1867, (1 Oct. 2020)

Jian, M., Jia, T., Wu, L. *et al.* Content-Based Bipartite User-Image Correlation for Image Recommendation. *Neural Process Lett* **52,** 1445–1459 (2020)

G. Guo, Y. Meng, Y. Zhang, C. Han and Y. Li, "Visual Semantic Image Recommendation," in IEEE Access, vol. 7, pp. 33424-33433, (2019)

Huang, Changqin, et al. "Large scale semantic web image retrieval using bimodal deep learning techniques." Information Sciences 430 (2018): 331-348.

Li, Huanyu. "A novel web image retrieval method: bagging weighted hashing based on local structure information." International Journal of Grid and Utility Computing 11.1 (2020): 10-20.

Kaushik, A.; Jacob, B.; Velavan, P. An Exploratory Study on a Reinforcement Learning Prototype for Multimodal Image Retrieval Using a Conversational Search Interface. *Knowledge* (2022), *2*, 116-138.

Hui Wu, Min Wang, Wengang Zhou, Houqiang Li, Qi Tian; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), (2022), pp. 9489-9498

Karamti, Hanen, Hadil Shaiba, and Abeer M. Mahmoud. "A deep locality sensitive hashing approach for achieving optimal image retrieval satisfaction." *International Journal of Electrical and Computer Engineering* 12.3 (2022): 2526.

Hyvönen, Eero, et al. "Ontology Based Image Retrieval." *WWW (posters)*. 2003.

Deepak, G., Kumar, N., Bharadwaj, G. V. S. Y., & Santhanavijayan, A. (2019, December). OntoQuest: an ontological strategy for automatic question generation for e-assessment using static and dynamic knowledge. In 2019 Fifteenth International Conference On Information Processing (ICINPRO) (pp. 1-6). IEEE.

Kaushik, I. S., Deepak, G., & Santhanavijayan, A. (2020). QuantQueryEXP: a novel strategic approach for query expansion based on quantum computing principles. Journal of Discrete Mathematical Sciences and Cryptography, 23(2), 573-584.

Hybridised, K. C. N. OntoKnowNHS: Ontology Driven Knowledge Centric Novel Hybridised Semantic Scheme for Image Recommendation Using Knowledge Graph. Knowledge Graphs and Semantic Web, 138.

Yethindra, D. N., & Deepak, G. (2021, September). A semantic approach for fashion recommendation using logistic regression and ontologies. In 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) (pp. 1-6). IEEE.

Deepak, G., & Santhanavijayan, A. (2022). UQSCM-RFD: a query–knowledge interfacing approach for diversified query recommendation in semantic search based on river flow dynamics and dynamic user interaction. Neural Computing and Applications, 34(1), 651-675.

Adithya, V., & Deepak, G. (2021, March). OntoReq: an ontology focused collective knowledge approach for requirement traceability modelling. In European, Asian, Middle Eastern, North African Conference on Management & Information Systems (pp. 358-370). Springer, Cham.

Vishal, K., Deepak, G., & Santhanavijayan, A. (2021). An approach for retrieval of text documents by hybridizing structural topic modeling and pointwise mutual information. In Innovations in Electrical and Electronic Engineering (pp. 969-977). Springer, Singapore.