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SERVICES FOR SCIENCE AND EDUCATION

Competitor Analysis Using Business Intelligence for Product Innovation

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Abstract

Competitor analysis and product innovation are important requirements for both strategic and operational management. The competitive characteristics of reviewers' comments are used to innovate and improve the product. The primary objective is to develop a comprehensive framework that intelligently learns from competitors' data and suggests innovative methods to aid the product to become a market leader with the help of artificial intelligence. The goal of this project is to create a model for analyzing and understanding the competitor's performance, its strengths, weakness, methods through various ways such as competitive attributes from consumers' perspectives, observation of the competitors' adverts etc. This model is expected to help in business decisions, a decision support system is created and help in the innovation of their product. The proposed system consists of the following modules: Trust computation module to compute the amount of trust in a product and its advertisements, Information storage module to store and process the video and image advertisements required efficiently, Video analytics module to derive key information from the filtered videos based on trust score, a Decision support system to make intelligent decisions for determining the multi-objective parameters for product innovation.

Keywords: Competitor Analysis; Product Innovation; Business Intelligence; Decision Support System.

INTRODUCTION

Competitor analysis presents multiple challenges namely misinterpretation of market requirements and getting overwhelmed with tons of data. It has always been dependent on customer centric data and product centric data has never been considered. Product innovation plays a crucial role in the development of a company but finding the right feature for the product proves to be a daunting task. This project aims at easing this process by analyzing the competitor's product's flaws and making use of that data for the respective company's product innovation. Competitor analysis is the practice of finding and studying competitors in various marketing techniques used by the industry. This information can be used to assess the company's strengths and weaknesses in comparison to each competitor. It is a key component of the company's strategy. It has been stated that most firms do not do this type of research in a systematic enough manner. Typical environmental scanning exposes many firms to harmful competitive blind spots due to a lack of robust competition research. To provide the best product or service to clients, it is necessary to do competition analysis at various phases of the organization. Comparing one's business, product, and service to those of competitors and identifying parallels and contrasts is what competitive analysis is all about. The most important step in starting a competitive study is deciding which rivals to investigate. Otherwise, the organization will waste a lot of time on competition research and come up with very little information. Product innovation refers to the development and subsequent introduction of a new or enhanced version of a prior item or service. It is the introduction of a new or considerably improved item or service in terms of its characteristics or intended application.. Product innovation allows companies to maintain market relevance while evolving and improving. A company's capacity to innovate is regarded as critical to its long-term success. When developing innovative goods, businesses must utilize their creativity and get out of their comfort zone to succeed. The keys to Product Development are well-defined decision-making procedures, decision making skills, encouraging innovation, creating phases based on outcomes, assessing performance using relevant metrics and overseeing funding.

The objective is to develop a comprehensive framework that analyses the "competitor's strength and weakness" and suggests improvement for development of the product that uses business intelligence for supply chain networks. The trust computation module computes the amount of trust in a product based on advertisements, product reviews, and ratings, and is followed by the information storage module, which efficiently stores and processes video and image advertisements, and a video analytics module, which derives key information from the video ads. Finally, a decision support system to make intelligent decisions for determining multi objective parameters for product innovation based on video analytics module inferences and trust scored based KPIs from the trust computation module.

LITERATURE SURVEY

Hutchinson et al. (2021)[12] focuses on self-innovating artificial intelligence (SAI). It is described as an organization's use of artificial intelligence (AI) to gradually improve existing products or produce new ones based on insights derived from continually combining and analyzing multiple data sources. Because SAI is about to fundamentally change how innovations are created, this article describes the underlying AI technology, conceptualizes and outlines how firms may incorporate SAI into their innovation processes in order to develop increasingly

complex products, and offers potential avenues for further research in this fascinating domain. Pati et al. (2021)[20] explores the impact of supportive and constructive feedback on inventive results during new product development, as well as the moderating influence of resource-constrained contexts, were investigated. Their research contributes to the current literature by outlining methods for improving inventive results in new product development in resource-constrained situations in emerging nations.

Choi et al. (2019)[4] study an innovative technique for detecting firm-level rivals through the construction of a network based on financial transactions between companies. The proposed method leverages the businesses with whom focal firms do business to give a data-driven depiction of focused enterprises' marketplaces and resources This article uses financial transactions of firms as examples of interfirm business operations to show a firm's implicit marketplaces with transactions to demanders and the firm's resources with transactions from suppliers.

Saideni et al. (2022)[22] evaluated and categorized many video compressive sensing systems based on neural networks. Compressive sensing has several uses, including medical imaging and remote sensing. CS is an efficient signal acquisition and reconstruction theory. Despite the lengthy training period, deep learning-based algorithms deliver speedy end-to-end video scene recovery with higher quality outcomes.

X. Ai et al. (2021)[2] developed a multi-modal information fusion-based system for video captioning that gathers and combines a variety of cues, including the original RGB data, optical flow data, and attribute tag data. To describe the movie and give more extensive and accurate description sequences, the model employs feature concatenation and attention techniques. Based on the combined data, the decoder was utilized to create caption phrases.

As a result, the above study promotes the adoption and exploitation of BI systems and their capabilities in broader organizational contexts. Despite the fact that businesses have been unable to fully use the benefits of BI systems for competitor analysis. They are mostly looking for ways to extract value from completed systems. Prior research, on the other hand, has not offered a comprehensive answer that examines the methods associated with the adoption and usage of BI systems in practical and sequential stages in financial settings. We propose a framework that, in addition to being a general and reusable abstraction, also includes particular functionality that aids in the building of BI apps, products, and solutions. [1-25]

PROPOSED WORK

This paper attempts to provide a comprehensive framework for competitor analysis and product innovation by assuming a modular structure. We present it through four sequential modules: Trust Computation, Information storage, Video analytics and Decision Support System. The trust computation module computes the amount of trust on a product based on the advertisements and product reviews and ratings .It is followed by the information storage module to store and process the video and image advertisements efficiently and a video analytics module to derive key information from the video ads. Finally, a decision support system to make intelligent decisions for determining the multi objective parameters for

product innovation based on the inferences from the video analytics module and trust scored based KPIs from the trust computation module.

Competitor Analysis using Business Intelligence for Product Innovation System Architecture

The proposed architecture consists of four modules namely Trust Computation, Information storage, Video analytics and Decision Support System. The first phase in the architecture is to gather and understand the competitor's product through customer reviews, product demonstration videos, and other means that will aid us in analyzing the competitor's products. Customer reviews and ratings, as well as picture and video marketing, are utilized to calculate the product's trustworthiness. The items are then screened based on a trust threshold before being processed and analyzed further. Using compressive sensing methods, the filtered data is efficiently stored. The video analytics module then gives an intermediate form of what is included in the commercials utilizing content captioning to establish the parameters to be given into the decision support system. Finally, the decision support system, in conjunction with ad analytics and client-centric evaluations and ratings, provides the parameters that must be tweaked to achieve the many objectives to create the product. The following system architecture Figure 1 shows the flow of the proposed system via 4 modules. Initially the input data used in the product's reviews and its advertisement video. Then based on the ratings present in the reviews, the trust computation module decides whether the product is viable for analysis or not based on the trust score. This is followed by storing of the video advertisement efficiently using the information storage module. Following that, the video analytics extracts information from the video using captioning. Based on that caption and the trust KPIs i.e. trust score and filtered reviews, the decision support system suggests multi objective parameters that can be used for innovating the product.

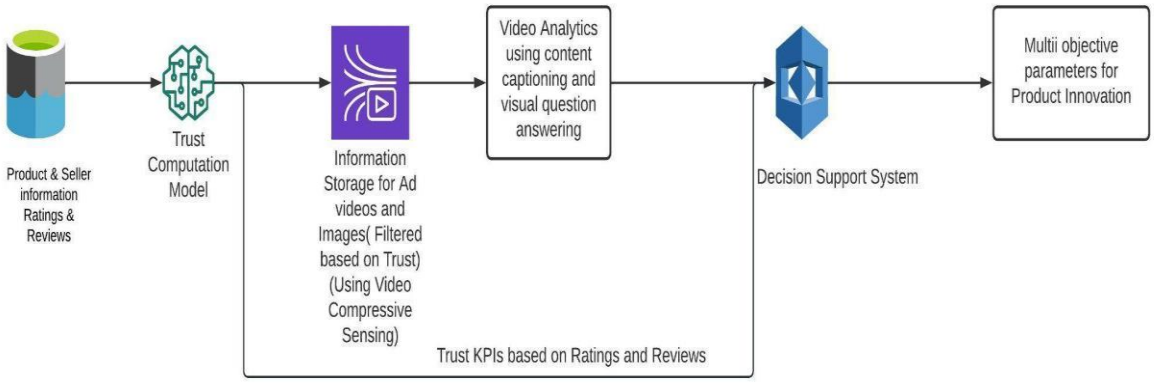


Fig. 1. Competitor Analysis using Business Intelligence for Product Innovation System Architecture

The proposed system is developed under the Anaconda - python environment and the training and testing were done on publicly available datasets. Initially for a given product, the trust score is computed based on the reviews and ratings given for it. Based on a threshold of the trust score, the product is judged to be viable for analysis or not. Then the product's advertisement videos

and product description videos are obtained and processed to be stored efficiently with the help of a compressive sensing algorithm. Based on the videos, conclusions about the product's parameters are derived using a content captioning model. Finally, based on the trust KPIs i.e. the trust score and the reviews of the same along with the conclusions drawn from the videos are fed into a decision support system which suggests the multi-objective parameters that can be used to innovate the product for the future.

Trust Computation Module

Product trust is an essential aspect when it comes to competitor analysis. The proposed algorithm aims to compute this trust on a product based on its reviews and ratings using a graph convergence. Everything can be represented using graphs now a days since each customer is reviewing more than one product and one product definitely interests more than one customer. So, a graph with nodes as the products and their reviews with their ratings as the weights is generated. The trust score is initialized based on the number of nodes present. Then in every iteration, it is updated based on the weights of the vertices and the previous iteration's value. It is then normalized to fit the rating scale. The iterations stop when the difference between the trust scores of the previous and current iterations is negligible or the number of iterations is greater than the specified number. The value of the last iteration is the product trust score and the decision of considering the product for analysis is decided based on a threshold value fixed earlier.

Algorithm: Compute Trust

Input: Graph, No. of iterations k, delta
Output: Trust Score
Initialize trust of all nodes to 1/v where v is number of vertices
for i from 1 to k:
for every node in the graph:
$trust_i$(node) = sum (weights of all incoming nodes)/$trust_{i-1}$(node)
Normalize scores to be in the range [1,5]
if($trust_i$(node) - $trust_{i-1}$(node)) < delta:
break loop
End

Advertisement Video Storage Module

Product advertisement videos are the primary legal source of competitor's data available for analysis. Following the analysis viability of the product, the advertisement videos of the product with a clear description the features of the product are collected and stored. When a video is stored and transmitted, it is basically reconstructed using compression and decompression. This is known as compressive sensing where the reconstruction of the video can be done with lesser number of frames than necessary according to the Nyquist – Shannon theorem. Compressive sensing can be done both spatially and temporally. Here, temporal approach is applied where a regression algorithm rebuilds the video frames with minimal resources possible. Initially the video is split into frames. Then, the split frames are mapped linearly for the construction of a measurement matrix. With the help of a measurement matrix, patch

extraction is done. The extracted patches are mapped to a non-linear block and then fed into a fully connected CNN with K hidden layers. This fully connected CNN then reconstructs the video by averaging the overlapped blocks.

Algorithm: Advertisement Video Storage

Input: Video with n frames V {v1, v2, v3, ……vn}
Output: Reconstructed video with n frames V {v1, v2, v3, ……vn}
Split video into frames wf x hf
Linear mapping of frames
Construct measurement matrix
Patch extraction: Extract patch from frame wp x hp
Mapping of a patch to a block (non – linear): Fully connected CNN with k hidden layers
Reconstruction: by averaging overlapping blocks.
End

Video Analytics for Identifying Product Parameters

The next step in competitor analysis is to identify the criteria that make the product competitive. These product criteria are identified by captioning the material provided in the commercial promotional videos. The product videos provide the necessary information about the product for analysis, such as its characteristics and metrics. The parameters are obtained utilizing a bidirectional flow construction network in this suggested technique. The preceding module's reconstruction of the product video is initially divided into frames. A CNN-based encoder is used to analyze the split frames in order to acquire semantic information. The encoded semantic information is then provided as a vector to a decoder, which uses an LSTM model to translate the semantic information into understandable phrases. The LSTM-based model creates the phrase by predicting the likelihood of the next word based on the probability of the previous word. The model then trains itself to lessen the loss and fixes the resulting caption's syntactical and semantic structures based on the loss. The final caption can be achieved when the loss is low. This caption is then used by the decision support system to suggest the parameters that can be suggested for innovation.

Algorithm: Identify product parameters

Input: Video with n frames V {v1, v2, v3, ……vn}
Output: Caption as a whole sentence S {s1, s2, s2, ….. , <EOS>}
Encode:
Input: Video frames {v1, v2, v3, …., vn}
Output: Features extracted with semantic info of Vi
Process video frame by frame
Extract semantic info using the CNN based encoder
Calculate loss for the extracted info
Re adjust weights based on loss
Extract features from the semantic info
Decode:

Input: Features extracted with semantic info of Vi
Output: Caption word by word S {s1, s2, s3, .. , <EOS>}
Predict i^{th} word using LSTM based on $(i-1)^{th}$ word
Calculate probability of the word using context vector
Assign weights based on temporal vectors
Adjust caption based on loss generated using log likelihood of temporal attention
Repeat till EOS occurs
Bi-directional flow constructor ():
Input: Hidden layer weights
Output: Loss function value
Calculate the best features based on the weight relevance and hidden layer weights
Best feature = Sum (Weight relevance * hidden layer weights)
Calculate loss using a distance metric by pooling features with a sigmoid of the LSTM components
Loss = Euclidean distance (mean pool (Video features), (Sigmoid (input, forget, memory, hidden, output))
Based on the loss generated, adjust the decoder weight values to generate the best caption
End

Decision Support System for Multi Objective Parameters:

Deep neural networks have lately become popular in recommender systems because of its capacity to simulate users' preferences. The attention mechanism of deep learning, in particular, enables recommender systems to integrate a wide range of features in a flexible manner. There are three inputs in particular for the proposal of multi objective parameters: user feedback The aggregate-based trust score and the caption of the product's marketing are important factors in objection suggestion. The decision support system, in conjunction with ad analytics and client-centric evaluations and ratings, gives the parameters that must be changed to fulfil the numerous product objectives. The decision support system proposes multi objective parameters that may be utilized for innovating the product

Algorithm: Multi Objective Parameter Suggestion

Input: Trust KPIs of product, caption of product video
Output: multi objective parameters
do:
shuffle the set of parameter terms in caption for the product
For each term:
Obtain matching trust KPI using attention
Compute loss based of degree of match
Update multi objective parameter list based on gradient descent
End for
Until convergence
End

RESULT

The datasets utilized are the freely available k-core Amazon reviews and ratings dataset [24] and the video advertising dataset [11]. The k-core amazon review dataset is a subset of the publicly accessible reviews and ratings of Amazon items, including at least k reviews for each item. It has over 20 million reviews for 786k goods. The 3477 videos in the video advertising dataset were utilized for training and testing. Videos taken from YouTube were utilized for validation. The trust computation and decision support system modules employed the reviews and ratings dataset by filtering based on the product id, while the information storage and video analytics modules used the video advertisement dataset by processing it frame by frame. For evaluating the first module, runtime was used as a metric. For the second module, we have used Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Metric (SSIM) as it is a compressive sensing task. The third module being a text-based task utilizes BLEU-4 score and METEOR score as metrics. The final module uses Area Under the Receiver Operator Characteristics (ROC) Curve (AUC) score as a metric for evaluation.

Trust Computation Module

The Trust Computation module focuses on computing the product trust based on product ratings. The proposed trust computation algorithm has an **average runtime of 7200 ms at 30 iterations**. The performance measure (runtime) compared with other existing graph convergence algorithms is given in the below graph. The graph contains the number of iterations in the x – axis and the runtime of the algorithm in the y – axis. The proposed trust computation algorithm is better than the existing algorithms because of the convergence and normalization parameters as clearly seen in the Figure 2 below

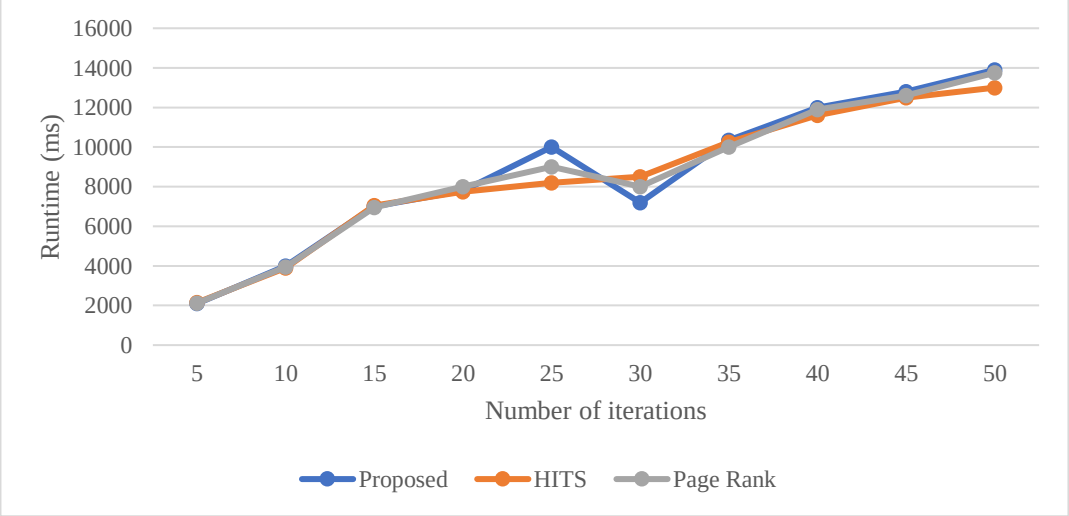


Fig. 2. Runtime comparison of proposed trust computation algorithm

Advertisement Video Storage Module

The advertisement video storage module stores the advertisement videos efficiently using a compressive sensing algorithm. The proposed compressive sensing algorithm has an average PSNR of 32.48. The performance measure (PSNR) compared with other existing compressive sensing algorithms is given in the below graph. The graph contains the method used in the x –

axis and the PSNR value of the method in the y – axis. The proposed compressive sensing algorithm has an average **PSNR of 32.48** which is better than the existing algorithms due to the averaging of overlapped patches approach as clearly seen in the Figure 3.

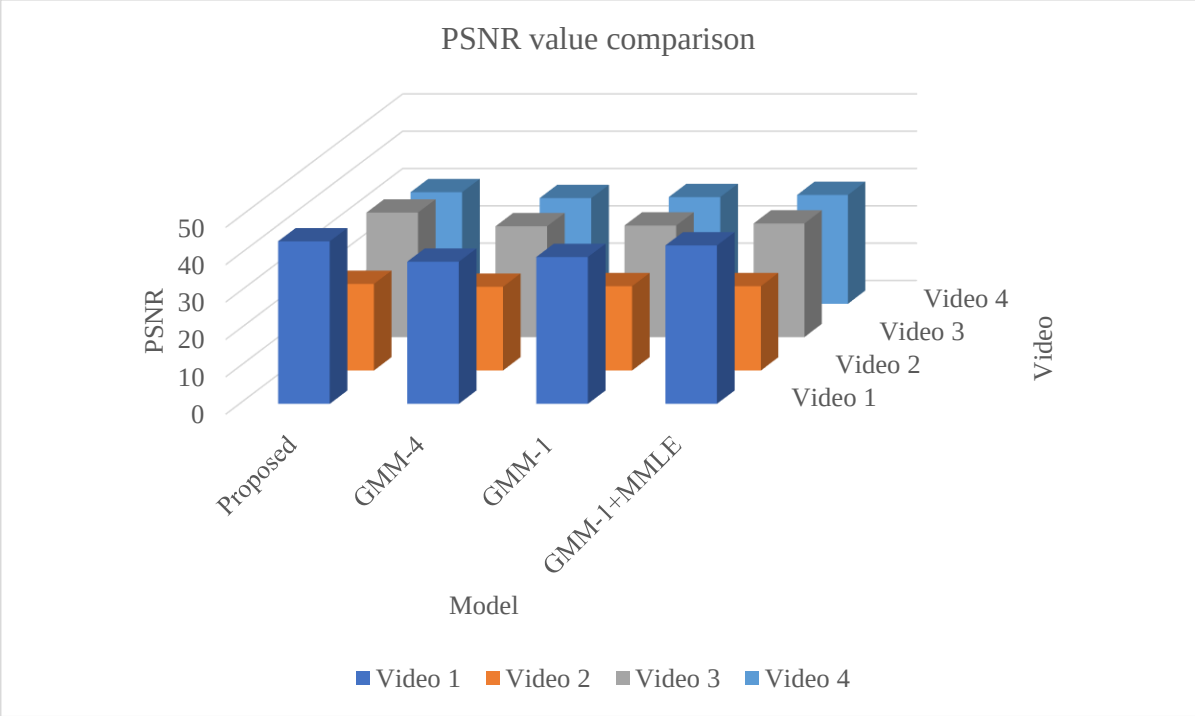


Fig. 3. PSNR values of compressive sensing algorithms for different videos

The proposed compressive sensing algorithm has an average SSIM of 0.869. The performance measure (SSIM) compared with other existing compressive sensing algorithms is given in the below graph. The graph contains the method used in the x – axis and the SSIM value of the method in the y – axis. The proposed compressive sensing algorithm has an average **SSIM of 0.869** is better than the existing algorithms due to the averaging of overlapped patches approach as clearly seen in the Figure 4 below

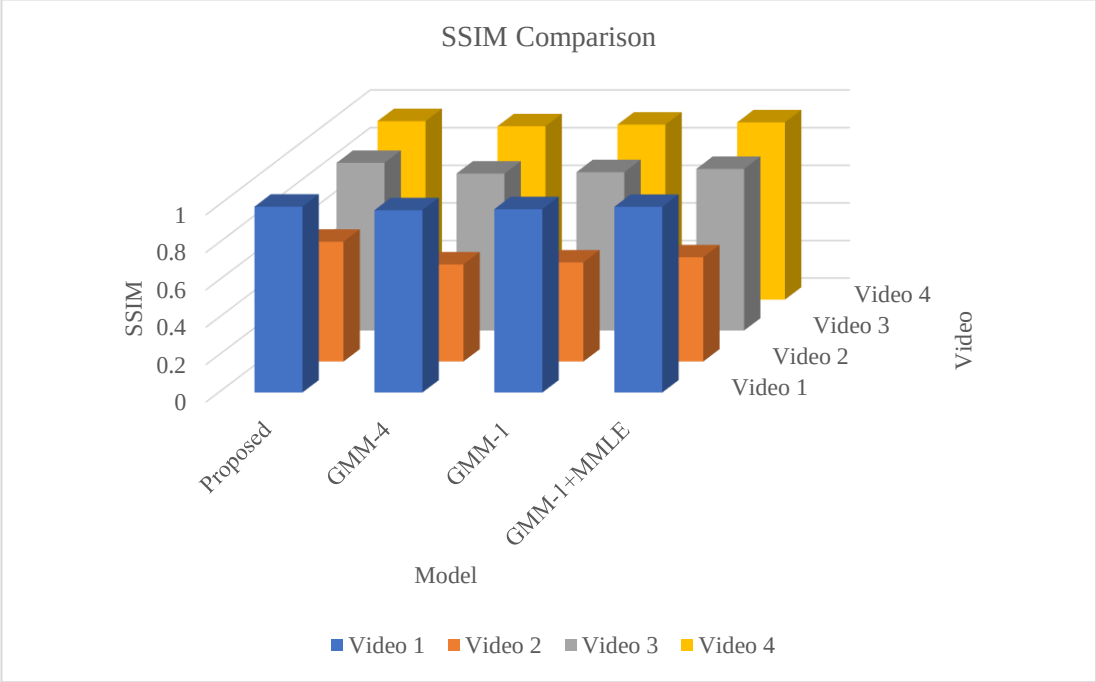


Fig. 4. SSIM values of compressive sensing algorithms for different videos

Video Analytics for Identifying Product Parameters

The Video Analytics module generates a caption based on the content of the product video. The proposed video analytics algorithm has an average BLEU – 4 score of 48. The performance measure (BLEU – 4 score) compared with other existing captioning algorithms is given in the below graph. The graph contains the method used in the x – axis and the BLEU - 4 value of the method in the y – axis. The proposed compressive sensing algorithm has an average **BLEU - 4 score of 48** is better than the existing algorithms due to the bi directional flow of reconstruction network as clearly seen in the Figure 5 below

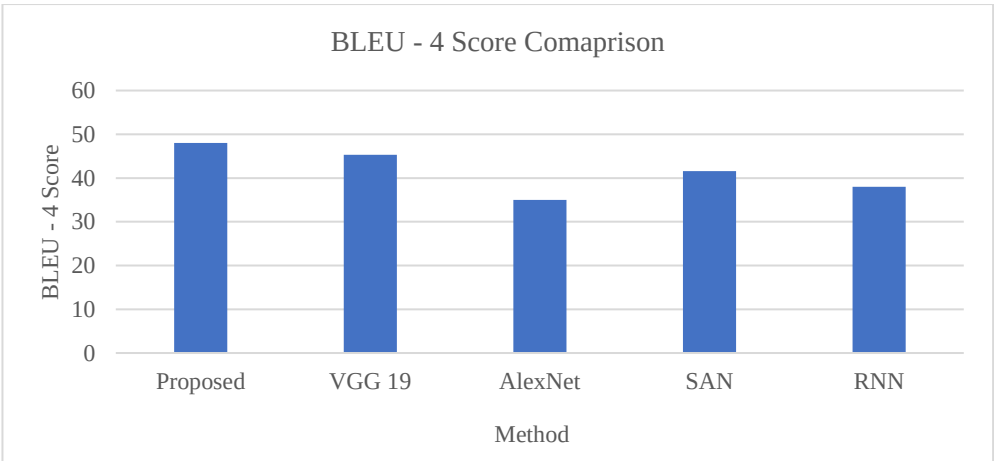


Fig. 5. BLEU - 4 values of different captioning algorithms

The proposed video analytics algorithm has an average METEOR score of 32. The performance measure (METEOR score) compared with other existing captioning algorithms is given in the

below graph. The graph contains the method used in the x – axis and the METEOR score value of the method in the y – axis. The proposed compressive sensing algorithm has an average **METEOR score of 32** is better than the existing algorithms due to the bi directional flow of reconstruction network as clearly seen in the figure 6 below

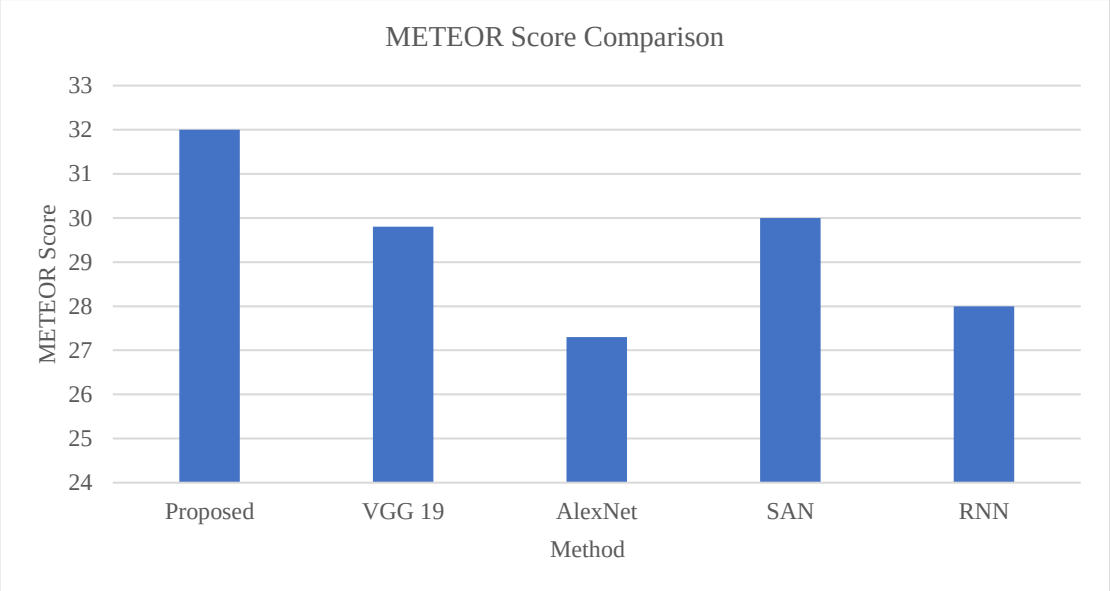


Fig. 6. METEOR scores of different captioning algorithms

Decision Support System for Multi Objective Parameters

The Decision Support System module suggests multi objective parameters based on the trust KPIs of the product and the caption for the content of the product video. The proposed DSS algorithm has an average AUC score of 87.8. The performance measure (AUC score) compared with other existing decision support system algorithms is given in the below graph. The proposed soft attention based DSS algorithm has an average AUC of 87.8 is better than the existing algorithms due to the soft attention mechanism of the network as clearly seen in the Figure 7 below.

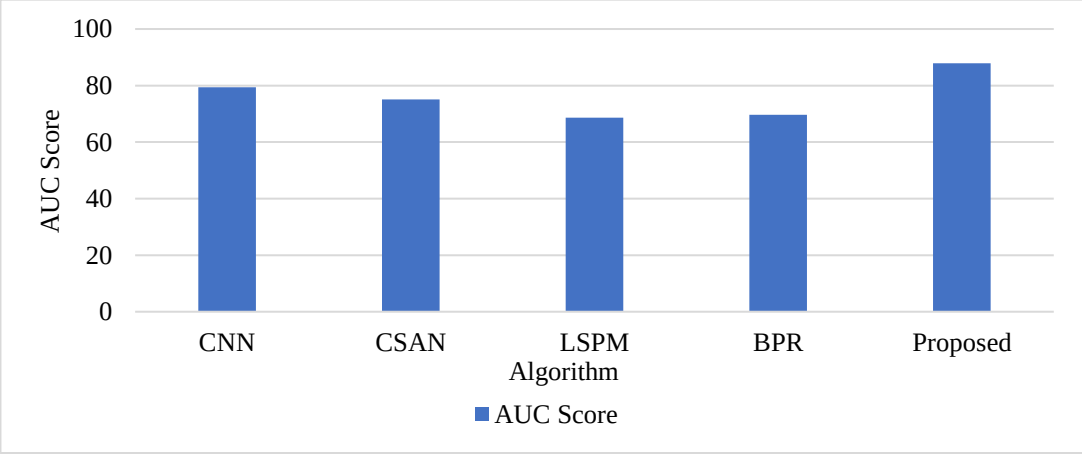


Fig. 7. AUC score comparison for Decision Support System module

CONCLUSION

Competitor analysis is necessary to stay relevant in the market. Product innovation refers to modifications that enhance the design, materials, and appearance of a product. The proposed method focuses on competitor analysis and production innovation for electronics. Initially for a given product, the trust score is computed based on the reviews and ratings given for it. Based on a threshold of the trust score, the product is judged to be viable for analysis or not. Then the product's advertisement videos and product description videos are obtained and processed to be stored efficiently with the help of a compressive sensing algorithm. Based on the videos, conclusions about the product's parameters are derived using a content captioning model. Finally, based on the trust KPIs i.e., the trust score and the reviews of the same along with the conclusions drawn from the videos are fed into a decision support system which suggests the multi-objective parameters that can be used to innovate the product for the future. This proposed work can be further extended to other types of products and industries. Also, analysis based on market state of the competitor and finances can be implemented in future along with additional ideas and approaches to provide assistance in achieving the goal. While analysing, competitor analysis can be broadened to cover more commodities and industries. Furthermore, future evaluations based on the competitor's market position and finances, as well as other concepts and methodologies, can be implemented. Because competing characteristics would benefit certain things more than others, the algorithm can widen its reach to extract competition aspects from specific customer ratings.

References

1. Afreen Farzana, U., Abirami, S. and Srivani, M. (2019). A Framework For Captioning The Human Interactions. 2019 11th International Conference on Advanced Computing (ICoAC). doi:10.1109/icoac48765.2019.246809.

2. Ai, X., Wang, H., Chen, H. and Xu, W. (2021). Video Captioning Method Based on Multi-Modal Information Fusion. 2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA). doi:10.1109/icaica52286.2021.9497899.
3. Chakraborti, S. and Dey, S. (2016). Multi-level K-means text clustering technique for topic identification for competitor intelligence. 2016 IEEE Tenth International Conference on Research Challenges in Information Science (RCIS). doi:10.1109/rcis.2016.7549332.

4. Choi, J., Tosyali, A., Kim, B., Lee, H. and Jeong, M.K. (2019). A Novel Method for Identifying Competitors Using a Financial Transaction Network. IEEE Transactions on Engineering Management, pp.1–16. doi:10.1109/tem.2019.2931660

5. Damianov, D. (2019). Lifecycle of Innovation and Life Cycle of an Innovative Product. 2019 International Conference on Creative Business for Smart and Sustainable Growth (CREBUS). [online] doi:10.1109/CREBUS.2019.8840060.

6. Fan, W., Han, S.-Y., Wu, W. and Sun, T. (2021). The Design Method of Product Innovation Model Based on Product Aesthetic Value. 2021 6th International Conference on Smart Grid and Electrical Automation (ICSGEA). doi:10.1109/icsgea53208.2021.00043.

7. Flor, M.L., Oltra-Mestre, M.J. and Sanjurjo, E.L. (2019). An Analysis of Open Innovation Strategies in Firms in Low and Medium Technology Industries. IEEE Transactions on Engineering Management, pp.1–15. doi:10.1109/tem.2019.2911253.

8. Gomes, P.J. and Silva, G.M. (2018). The Value of Supply Network for Product Innovation. IEEE Engineering Management Review, 46(4), pp.36–45. doi:10.1109/emr.2018.2883617.

9. Guan, W., Fan, H., Xu, L. and Wang, Y. (2018). A nonlocal patch-based video compressive sensing recovery algorithm. 2018 37th Chinese Control Conference (CCC). doi:10.23919/chicc.2018.8483925.

10. Guo, Q., Xu, Y. and Gao, S. (2021). Recorrect Net: Visual Guidance for Image Captioning. 2021 7th IEEE International Conference on Network Intelligence and Digital Content (IC-NIDC). doi:10.1109/ic-nidc54101.2021.9660494.

11. Hussain, Z., Zhang, M., Zhang, X., Ye, K., Thomas, C., Agha, Z., Ong, N. and Kovashka, A. (n.d.). Automatic Understanding of Image and Video Advertisements. [online]

12. Hutchinson, P. (2020). Reinventing Innovation Management: The Impact of Self-Innovating Artificial Intelligence. IEEE Transactions on Engineering Management, pp.1–12. doi:10.1109/tem.2020.2977222.

13. Jayasinghe, U., Truong, N.B., Lee, G.M. and Um, T.-W. (2016). RpR: A Trust Computation Model for Social Internet of Things. 2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld). doi:10.1109/uic-atc-scalcom-cbdcom-iop-smartworld.2016.0146.

14. Jin, J., Guo, M. and Zhang, Z. (2019). Selective Adoption of Open Innovation for New Product Development in High-Tech SMEs in Emerging Economies. IEEE Transactions on Engineering Management, [online] pp.1–9. doi:10.1109/TEM.2019.2948739.

15. Kronemeyer, L.L., Eilers, K., Wustmans, M. and Moehrle, M.G. (2020). Monitoring Competitors' Innovation Activities: Analyzing the Competitive Patent Landscape Based on Semantic Anchor Points. IEEE Transactions on Engineering Management, pp.1–16. doi:10.1109/tem.2019.2958518.

16. Larsson, L. and Romero, D. (2017). Expanding the industrial design space through production innovation(s). 2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC). doi:10.1109/ice.2017.8279946.

17. Lee, Y. (2022). Identifying Competitive Attributes Based on an Ensemble of Explainable Artificial Intelligence. Business & Information Systems Engineering. doi:10.1007/s12599-021-00737-5.

18. Leong, L.-Y., Hew, T.-S., Ooi, K.-B. and Dwivedi, Y.K. (2020). Predicting trust in online advertising with an SEM-artificial neural network approach. Expert Systems with Applications, p.113849. doi: 10.1016/j.eswa.2020.113849.

19. Ni, J., Li, J. and Mcauley, J. (n.d.). Justifying Recommendations using Distantly-Labeled Reviews and Fine-Grained Aspects.

20. Pati, R. and Garud, N. (2021). Role of Feedback on Innovative Outcomes: Moderating Role of Resource-Constrained Environments. IEEE Transactions on Engineering Management, [online] 68(3), pp.685–698. doi:10.1109/TEM.2020.3015129.

21. Rimle, P., Dogan-Schonberger, P. and Gross, M. (2021). Enriching Video Captions with Contextual Text. 2020 25th International Conference on Pattern Recognition (ICPR). doi:10.1109/icpr48806.2021.9412008.

22. Saideni, W., Helbert, D., Courreges, F. and Cances, J.-P. (2022). An Overview on Deep Learning Techniques for Video Compressive Sensing. Applied Sciences, 12(5), p.2734. doi:10.3390/app12052734.

23. Velmurugan, K., Yuvaraj, S., Sumalatha, M.R. and Palivela, L. (2022). Supply Chain Financial Risk Management Using Business Intelligence. SSRN Electronic Journal. doi:10.2139/ssrn.4128710.

24. Yang, M. and Jiang, P. (2017). An integrated pattern using different innovation methods for makers' product development. 2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE). doi:10.1109/iske.2017.8258800.

25. Zhang, M., Fan, B., Zhang, N., Wang, W. and Fan, W. (2021). Mining product innovation ideas from online reviews. Information Processing & Management, 58(1), p.102389. doi: 10.1016/j.ipm.2020.102389.