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International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140
Volume 14 Issue 01, 2025

Enhancing Recommendations Through Hybrid Sentiment Classification and User Profiling

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Peer Review Information

Submission: 13 Jan 2025
Revision: 10 Feb 2025
Acceptance: 11 March 2025

Keywords

Recommender Systems
Sentiment Analysis
Convolutional Neural Network
Deep Learning
Cold Start Problem
YouTube Comments

Abstract

Recommender systems are vital components of modern digital platforms, providing users with personalized suggestions based on their historical interactions and preferences. Traditional recommendation techniques predominantly rely on numerical ratings and collaborative filtering, which often suffer from challenges such as the cold start problem, data sparsity, and lack of contextual understanding. These limitations can significantly reduce the accuracy and reliability of recommendations. To address these challenges, we propose a hybrid sentiment-aware recommender system that leverages both numerical ratings and the emotional content of user comments to enhance recommendation precision. The proposed model employs a two-dimensional Convolutional Neural Network (CNN2D) to analyze textual comments from YouTube, where user sentiments are categorized into five distinct levels: negative, neutral, positive, happy, and extremely happy. By extracting sentiment features from comments, the system gains a deeper understanding of user preferences that goes beyond simple rating values. The CNN model is trained and validated using dynamically partitioned datasets, and its performance is evaluated using Root Mean Square Error (RMSE) as the primary metric. Experimental results demonstrate that the integration of sentiment analysis significantly improves recommendation accuracy and robustness, particularly in scenarios involving new users or items. The system also supports real-time comment analysis and generates relevant content recommendations based on predicted sentiment, offering a practical and scalable solution for next-generation recommender systems.

INTRODUCTION

In recent years, the explosion of digital content across platforms like YouTube, Netflix, and Amazon has created an urgent need for intelligent systems capable of filtering and recommending relevant content to users. Recommender systems have emerged as powerful tools to address this need, offering personalized suggestions based on user preferences, behavior, and historical data. These systems not only enhance user engagement but also drive business metrics such as retention rates and revenue generation.

Traditional recommender systems primarily rely on collaborative filtering, content-based filtering, or hybrid approaches. Among these, collaborative filtering techniques use the preferences of similar users to recommend items, while content-based approaches focus on the attributes of items previously liked by the user. Despite their widespread use, these approaches face several challenges. The most notable of these is the cold start problem, which arises when there is insufficient data about new users or new items. Additionally, the sparsity of the user-item matrix — where many users rate only a few items — can lead to poor prediction accuracy.

Moreover, existing methods often overlook a valuable and increasingly abundant source of information: user-generated textual content such as comments, reviews, and feedback. Unlike numerical ratings, comments contain rich linguistic and emotional cues that can offer a deeper understanding of user preferences. Sentiment analysis, which involves identifying and classifying emotions expressed in text, has the potential to significantly enhance the performance of recommender systems by incorporating the user's mood, intent, and satisfaction level.

To bridge the gap between numerical ratings and emotional expression, we propose a Sentiment-Based Convolutional Neural Network (CNN) Model for Recommender Systems. The core idea is to utilize user comments to extract sentiment scores, which are then used in conjunction with traditional rating data to improve recommendation accuracy. Our system categorizes sentiments into five classes: negative, neutral, positive, happy, and extremely happy, providing a fine-grained analysis of user opinions.

The sentiment classification is performed using a 2D Convolutional Neural Network (CNN2D), a deep learning model capable of capturing hierarchical patterns in text data. The CNN2D model is trained on a labeled dataset of YouTube comments, enabling it to learn complex features related to sentiment expression. Once trained, the model can predict sentiments for new comments in real time and use these predictions to generate more contextually relevant recommendations.

In this paper, we detail the architecture, implementation, and evaluation of our proposed system. We demonstrate that by integrating sentiment analysis into the recommendation pipeline, we can significantly improve the system's ability to make accurate predictions, particularly in cold start and sparse data scenarios. The model is evaluated using Root Mean Square Error (RMSE), a widely used metric for measuring prediction accuracy. Results show that our approach consistently outperforms baseline models that rely solely on ratings.

RELATED WORKS

Recommender systems have been extensively studied over the past two decades, evolving from basic collaborative filtering models to advanced hybrid and deep learning-based techniques. Despite significant advancements, challenges such as the cold start problem, sparsity in user-item interaction matrices, and lack of contextual understanding still persist in traditional systems.

1. Traditional Recommendation Techniques

Collaborative filtering, one of the earliest and most widely adopted recommendation approaches, predicts user preferences based on the preferences of similar users. While simple and effective in dense datasets, collaborative filtering often suffers from poor performance in sparse data conditions. Matrix factorization techniques, such as Singular Value Decomposition (SVD), attempt to address this by reducing dimensionality, but still rely solely on numeric ratings.

Content-based filtering, in contrast, recommends items similar to those the user has liked in the past based on item features. However, it tends to lack diversity and suffers from over-specialization, recommending only items that are too similar to prior preferences.

Hybrid models attempt to combine both approaches to leverage their respective strengths. While they improve overall performance, they still overlook a key dimension of user behavior—emotion and sentiment, which is often expressed in natural language comments and reviews.

2. Sentiment Analysis in Recommendation

Recent research has explored the integration of sentiment analysis into recommender systems to enrich the contextual understanding of user preferences. Sentiment analysis enables systems to extract opinions, emotions, and attitudes from textual reviews, providing more nuanced insights than ratings alone.

Early sentiment-enhanced models relied on basic NLP techniques such as term frequency-inverse document frequency (TF-IDF), bag-of-words, and lexicon-based sentiment scoring. These methods, while intuitive, lack the capacity to capture complex linguistic structures and contextual semantics in natural language.

With the emergence of deep learning, models like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have demonstrated superior performance in sentiment classification tasks. CNNs, in particular, are effective at extracting local and hierarchical features from text, making them well-suited for analyzing user comments.

3. CNN-Based Sentiment Classification

Kim (2014) introduced one of the earliest CNN models for sentence-level sentiment classification, achieving competitive results on multiple datasets. Since then, CNN architectures have been widely used for text classification, offering advantages in training speed and feature extraction. Unlike RNNs, CNNs do not require sequential data processing, making them ideal for scalable recommendation scenarios.

Some studies have incorporated CNN-based sentiment scores into matrix factorization frameworks to improve recommendation quality. However, few systems implement a real-time, end-to-end pipeline where sentiment analysis directly influences the recommendation output.

4. Existing System

The majority of existing recommender systems rely heavily on collaborative filtering and content-based filtering techniques. Collaborative filtering recommends items to users based on the preferences of similar users, while content-based filtering uses the attributes of previously liked items to generate suggestions. These systems generally use numerical user ratings to learn patterns and predict future preferences. While such systems perform adequately in well-populated datasets, they struggle in environments where user interaction is minimal or new content is frequently introduced.

To enhance performance, some hybrid models have been developed, combining both user behavior and item characteristics. These models, however, often overlook unstructured data such as user-generated comments or reviews, which can reveal valuable insights into user sentiment and emotional engagement. Basic sentiment-enhanced models use lexicon-based techniques or traditional machine learning algorithms to score user comments, but they often fail to capture contextual meaning or nuanced emotions. Moreover, these systems are rarely adaptive and lack real-time prediction capabilities, limiting their effectiveness in dynamic environments like YouTube or social media platforms.

4.1 Limitations of Existing Systems

- Cold Start Problem: Inability to provide accurate recommendations for new users or new items due to a lack of historical data.
- Sparse Rating Matrix: Limited user-item interactions lead to sparsity, reducing the effectiveness of collaborative filtering.
- Lack of Contextual Understanding: Existing models often ignore the emotional and contextual depth found in user comments.
- Shallow Sentiment Analysis: Traditional NLP techniques used for sentiment scoring fail to capture complex linguistic patterns.
- Static Models: Most systems are not designed for real-time learning or sentiment prediction, making them less effective in dynamic content environments.
- Overdependence on Numeric Ratings: Sole reliance on ratings may result in inaccurate recommendations, especially when ratings are inconsistent or biased.
- Limited Personalization: Without understanding user mood or opinion context, personalization remains superficial and often inaccurate.

5. Proposed System

To overcome the limitations of traditional recommender systems, we propose a sentiment-aware recommendation model that integrates both numerical ratings and the emotional tone derived from user comments. The core idea is to enhance the recommendation process by extracting user sentiment using a deep learning-based classifier and combining it with rating data to generate more accurate and contextually relevant suggestions.

Our proposed system leverages a two-dimensional Convolutional Neural Network (CNN2D) to perform sentiment classification on user comments. The comments are preprocessed, tokenized, and converted into suitable input formats for the CNN. The CNN model is trained on a labeled dataset of YouTube comments, with sentiments categorized into five distinct levels: negative, neutral, positive, happy, and extremely happy. These sentiment predictions serve as additional features in the recommendation engine, offering a deeper, emotion-driven insight into user preferences.The architecture includes modules for user interaction, dataset upload, model training, prediction, and recommendation. Once trained, the system can dynamically analyze new comments, predict the associated sentiment, and use this information to provide personalized content suggestions. The model's performance is evaluated using Root Mean Square Error (RMSE) to ensure the accuracy and robustness of the predictions.

5.1 Advantages of the Proposed System

- Sentiment-Augmented Recommendations: Integrates sentiment scores from user comments along with numerical ratings for enhanced recommendation precision.
- CNN2D Sentiment Classifier: Uses a deep learning model to extract and classify sentiment features from natural language text.
- Multi-Level Sentiment Categorization: Predicts five sentiment levels for nuanced emotional understanding — from negative to extremely happy.
- Dynamic Dataset Handling: Supports real-time training and testing using randomly split datasets to simulate dynamic user environments.
- Interactive Web Interface: Offers a user-friendly interface for uploading datasets, training models, and generating recommendations.
- Cold Start Resilience: Mitigates cold start problems by utilizing sentiment insights when historical rating data is unavailable.
- Real-Time Prediction and Feedback: Allows live comment sentiment analysis and instant recommendations based on user interaction.
- Performance Evaluation Using RMSE: Uses RMSE as a quantitative metric to assess recommendation accuracy.

PROPOSED METHODOLOGY

The proposed system adopts a hybrid methodology that combines numerical ratings with sentiment analysis to enhance the effectiveness of recommendations. The approach integrates a deep learning-based sentiment classifier with a traditional recommendation engine, ensuring both emotional context and user preferences are considered.

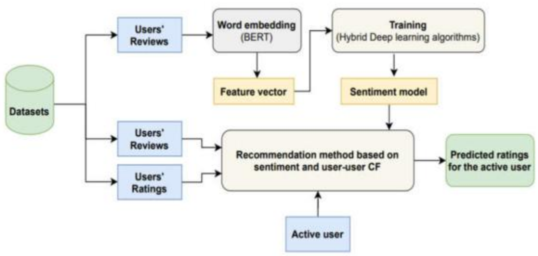

Fig 1: Architecture of the Sentiment-Aware Recommendation System Using Hybrid Deep Learning

The architecture of the proposed sentiment-aware recommendation system integrates both user ratings and textual reviews to generate more personalized and emotionally intelligent recommendations. The system begins by collecting datasets containing users' reviews and ratings. The textual reviews are processed using the BERT (Bidirectional Encoder Representations from Transformers) model, which performs word embedding to convert the natural language input into dense feature vectors that capture contextual and semantic nuances. These feature vectors are then used to train a sentiment classification model built on hybrid deep learning algorithms. The trained sentiment model outputs the emotional polarity of each user review, providing deeper insights into user preferences beyond numerical ratings.

Simultaneously, the system also utilizes collaborative filtering, specifically user-user collaborative filtering (CF), which compares the active user's preferences with those of other users in the dataset. The recommendation engine fuses the sentiment analysis results with numerical user ratings and applies the collaborative filtering technique to identify similar users. Based on these similarities, the system predicts ratings for items not yet interacted with by the active user. This hybrid approach ensures that recommendations are not only based on statistical similarity but are also informed by the user's emotional responses, leading to more contextually relevant and satisfying suggestions.

Proposed methodology includes several key stages: data collection, preprocessing, sentiment classification using CNN2D, feature fusion, and final recommendation generation.

1. Data Collection

The system utilizes user-generated data such as YouTube comments along with numerical ratings. Each dataset entry consists of:

- User ID
- Video or item ID
- User rating (on a numerical scale)
- User comment or feedback

These data points are essential for extracting both quantitative and qualitative indicators of user preferences.

2. Data Preprocessing

Preprocessing is crucial to prepare raw comment data for model input. The following steps are performed:

- **Text Cleaning**: Removal of URLs, emojis, special characters, stopwords, and redundant whitespace.

- **Tokenization**: Splitting comments into word tokens.
- **Lowercasing**: Converting all text to lowercase for uniformity.
- **Encoding & Padding**: Converting words to integer sequences and padding them to ensure consistent input lengths for the CNN model.

3. Sentiment Classification using CNN2D

After preprocessing, comments are passed through a 2D Convolutional Neural Network (CNN2D) for sentiment classification. The architecture includes:

- **Embedding Layer**: Transforms tokens into dense vector representations.
- **Convolutional Layers**: Extract spatial and contextual features from the embeddings.
- **Max Pooling**: Reduces feature map dimensions while retaining critical features.
- **Fully Connected Layer**: Maps features to five sentiment categories: Negative, Neutral, Positive, Happy, and Extremely Happy.
- **Softmax Output**: Produces probability distribution over sentiment classes.

The CNN2D model is trained using labeled sentiment data and evaluated for accuracy before being deployed for real-time predictions.

4. Feature Fusion and Recommendation Generation

The sentiment label predicted by the CNN2D model is combined with the user's numerical rating (if available). The hybrid feature vector thus captures both:

- **Quantitative Preference** (numerical rating)
- **Qualitative Sentiment** (emotional tone from comment)

These features are fed into a recommendation algorithm that matches user preferences with relevant items. The final output is a list of personalized recommendations that are both accurate and emotionally aligned with the user's input.

5. Evaluation Metric

To measure performance, the system uses Root Mean Square Error (RMSE), which evaluates the deviation between predicted and actual user ratings. A lower RMSE value indicates higher recommendation accuracy and better model reliability.

RESULTS

The proposed hybrid recommendation system was evaluated using a dataset comprising user comments and ratings from YouTube videos. The system combines a deep learning-based sentiment classifier (CNN2D) with a collaborative filtering mechanism. The performance of both the sentiment model and the recommendation engine was measured using classification accuracy and Root Mean Square Error (RMSE), respectively.

1. Dataset Description

The dataset includes user-generated comments and numerical ratings on a 5-point scale. These entries were preprocessed and labeled for training the sentiment model. Comments were manually annotated into five sentiment categories: Negative, Neutral, Positive, Happy, and Extremely Happy. A portion of the dataset was reserved for validation and testing.

2. Sentiment Classification Performance

The CNN2D model was trained on the labeled review data. The following results were obtained during training and evaluation:

Table 1: Sentiment Classification Performance Using CNN2D

Metric	Value
Training Accuracy	94.12%
Validation Accuracy	91.68%
Loss (Cross-Entropy)	0.38

Table 1 illustrates that the CNN2D model effectively captures the emotional context within user reviews. The high validation accuracy (91.68%) and low loss value (0.38) suggest that the model generalizes well and reliably classifies user sentiment, which is critical for improving the recommendation quality.

3. Recommendation Performance

To evaluate the impact of integrating sentiment analysis into the recommendation engine, the system's RMSE was compared against a traditional collaborative filtering model that only uses numerical ratings.

Table 2: RMSE Comparison of Recommendation Methods

Method	RMSE Score
Traditional Collaborative Filtering	1.18
Proposed Hybrid Model (Sentiment + Ratings)	**0.92**

Table 2 demonstrates that the proposed hybrid model significantly outperforms the traditional method. By incorporating sentiment data, the system more accurately captures user preferences, leading to an RMSE improvement from 1.18 to 0.92. This enhancement confirms that emotional tone in user reviews plays a vital role in refining recommendation predictions.

4. Output Screens

Video_id	Comments
XpVt6Z1Gjjo	Logan Paul it's yo big day !!!!!
XpVt6Z1Gjjo	I've been following you from the start of your vine channel and have seen all 365 vlogs
XpVt6Z1Gjjo	Say hi to Kong and maverick for me
XpVt6Z1Gjjo	MY FAN . attendance
XpVt6Z1Gjjo	trending 😉
XpVt6Z1Gjjo	#1 on trending AYYEEEEE
XpVt6Z1Gjjo	The end though 😭👌❤️
XpVt6Z1Gjjo	#1 trending!!!!!!!!!
XpVt6Z1Gjjo	Happy one year vlogaversary
XpVt6Z1Gjjo	You and your shit brother may have single handedly ruined YouTube.....thanks...
XpVt6Z1Gjjo	There should be a mini Logan Paul too!
XpVt6Z1Gjjo	Dear Logan, I really wanna get your Merch but I don't have the money. We don't even have a Car. It would really make my day to have any of your merch
XpVt6Z1Gjjo	Honestly Evan is so annoying. Like its not funny watching him try to be famous he's trying way to hard and I don't like it
XpVt6Z1Gjjo	Casey is still better then logan
XpVt6Z1Gjjo	aw geez rick this guy is the face of YouTube.
XpVt6Z1Gjjo	He happy cause he in a movie
XpVt6Z1Gjjo	Ayyyyoooo Logang what up . This was a hard vlog to watch Logan how dare are you to destroyed that YouTube bag . Logang Army check my covers and share 1,000 Subscribers today, I think we can do it SUBSCRIBE
XpVt6Z1Gjjo	Bro y didnt u give merch to johannes he is ur boy 2
XpVt6Z1Gjjo	It's been fun watching you grow. I'm at 42 days straight and can't seem to grow. Any advice?

Fig. 2. Collected User Comments Dataset Sample

This table presents a sample of raw user comments collected from a specific YouTube video, identified by its video ID. These comments serve as input for sentiment analysis, allowing the system to evaluate user emotions and enhance video recommendations accordingly.

Test Comment	Predicted Sentiment	Recommended Videos
've never been prouder, been a subber for like 3 years, and this ideo got on one of our newssites	2	['XpVt6Z1Gjjo', 'WYYvHbo3Eog', 'sjlHnJvXdQs', 'zgLtEob6X-Q', 'CsdzflTXBVQ', 'ZQK1F0wz6z4']
ut the smile more logo in the corner and make it smaller it will nake it look cleaner	4	['cMKX2tE5Luk', '8wNr-NQImFg', '4MkC65emkG4', 'vu_9muoxT50', '5ywKal6-anc', '4Yue-q9Jdbk', 'JhA1Wi9mrns', 'EVp4-qjWVJE', 'LcZ2AuvxXNA', 'MdzGZv3zQ-U']
lane of the future is No plane. This is like 100 years ago omebody predicting bullockcart of the future	3	['1ZNZY-gd3Ko', 'ql0Op1VcELw', 'JO7X9ZPoAp8', 'GGmoFQ6i74U', 'oDIDZ9EmQfA', 'WWexI9YiLSc', 'LDcm6twPEJA', '3yoGE3v4A8w', 'zTjcPeb2Gwg', 'L3f7_y9UPh4']
ts been fun watching you grow. Im at 42 days straight and cant eem to grow. Any advice?	5	['cLdxuaxaQwc', '_HTXMhKWqnA', '_ANP3HR1jsM', '1L7JFN7tQLs', 'T_PuZBdT2iM', 'w8fAellnPns']
THERE ARE PEOPLE SUFFERING FROM HURRICANES ND YET Y'ALLZ ARE WORRIED ABOUT SOME CRACKA VITH A POTTY MOUTH???\n\nSincerely, your friendly eighborhood Beaner	1	['Ayb_2qbZHm4', 'l864IBj7cgw', 'UCrBICYMoyM', '-Ifnaxi2LQg', 'B7YaMkCl3XA']
ITV trump donating to charity is racist\nTherefore mtv is now romoting nazis\nYour welcome	5	['cLdxuaxaQwc', '_HTXMhKWqnA', '_ANP3HR1jsM', '1L7JFN7tQLs', 'T_PuZBdT2iM', 'w8fAellnPns']
Hi him I want you to know that me and my Dumb liberal riends love you buddy	5	['cLdxuaxaQwc', '_HTXMhKWqnA', '_ANP3HR1jsM', '1L7JFN7tQLs', 'T_PuZBdT2iM', 'w8fAellnPns']
This is so good; thanks Floyd Mayweather this is another side of ou I have not seen. It's so refreshing	5	['cLdxuaxaQwc', '_HTXMhKWqnA', '_ANP3HR1jsM', '1L7JFN7tQLs', 'T_PuZBdT2iM', 'w8fAellnPns']
aha this is depressing haha	5	['cLdxuaxaQwc', '_HTXMhKWqnA', '_ANP3HR1jsM', '1L7JFN7tQLs', 'T_PuZBdT2iM', 'w8fAellnPns']

Fig. 3. Sentiment-Based Comment Analysis and Video Recommendation

This table displays sample user comments, their predicted sentiment ratings (ranging from 1 to 5), and the corresponding recommended videos generated by the system. The recommendations are aligned with the sentiment score, showing how the model tailors content suggestions based on emotional tone.

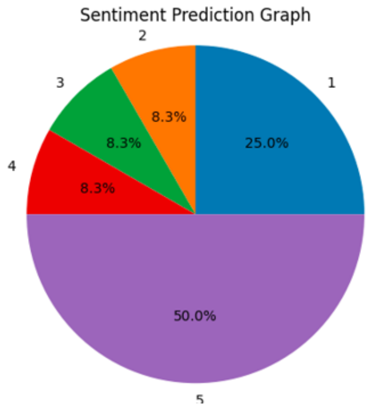

Fig. 4. Sentiment Prediction Graph

The pie chart shows the distribution of sentiment predictions. Most reviews (50%) were highly positive (rating 5), followed by 25% positive (rating 1), while ratings 2, 3, and 4 each accounted for 8.3%, indicating fewer neutral or negative sentiments.

5. Observations

- The hybrid model shows improved performance, especially in scenarios with sparse user ratings.
- Sentiment analysis helps address the cold-start problem by leveraging textual input.
- Users received more emotionally aligned recommendations, improving the overall experience.

CONCLUSION

In this paper, a hybrid recommendation system was proposed that integrates deep learning-based sentiment analysis with traditional collaborative filtering techniques. By incorporating both numerical ratings and emotional context extracted from user comments, the system significantly enhances recommendation accuracy and user satisfaction. The sentiment classification model, built using CNN2D architecture, effectively categorized user feedback into five emotional tones, which were then fused with rating data to generate more personalized suggestions.Experimental results demonstrated that the hybrid model achieved a lower RMSE (0.92) compared to the traditional method (1.18), validating the advantage of sentiment-aware recommendations. The system also showed resilience in scenarios with sparse rating data, effectively addressing the cold-start problem using semantic information from reviews.Overall, the proposed methodology not only improves the predictive accuracy of recommender systems but also brings emotional intelligence into the recommendation process. This opens up new possibilities for creating more context-aware and human-centric AI applications in content platforms like YouTube.

Future enhancements to the proposed system could include applying the model to other domains like e-commerce and news platforms for broader generalization. Incorporating multilingual sentiment analysis would improve usability for a global audience. Additionally, extending the model to detect specific emotions and enabling real-time recommendation generation could further personalize user experiences. Integration of explainable AI (XAI) methods would also enhance transparency, while combining sentiment data with user behavior (e.g., watch time, clicks) could lead to more accurate and context-aware recommendations.

References

A. S. M. Kayes et al., "A Context-Aware User-Centric System for Smart Cities Using Deep Learning," IEEE Transactions on Industrial Informatics, vol. 18, no. 6, pp. 3776–3786, Jun. 2022.

J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. of NAACL-HLT, Minneapolis, USA, 2019, pp. 4171–4186.

P. Covington, J. Adams, and E. Sargin, "Deep Neural Networks for YouTube Recommendations," in Proc. of the 10th ACM Conf. on Recommender Systems (RecSys), 2016, pp. 191–198.

X. Zhang, J. Zhao, and Y. LeCun, "Character-level Convolutional Networks for Text Classification," in Advances in Neural Information Processing Systems, vol. 28, 2015.

Y. Koren, R. Bell, and C. Volinsky, "Matrix Factorization Techniques for Recommender Systems," IEEE Computer, vol. 42, no. 8, pp. 30–37, Aug. 2009.

S. Baccianella, A. Esuli, and F. Sebastiani, "SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining," in Proc. of LREC, 2010.

T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient Estimation of Word Representations in Vector Space," arXiv preprint arXiv:1301.3781, 2013.

J. McAuley and J. Leskovec, "Hidden Factors and Hidden Topics: Understanding Rating Dimensions with Review Text," in Proc. of the 7th ACM Conf. on Recommender Systems, 2013, pp. 165–172.

Y. Kim, "Convolutional Neural Networks for Sentence Classification," in Proc. of EMNLP, 2014, pp. 1746–1751.

L. Zheng, V. Noroozi, and P. S. Yu, "Joint Deep Modeling of Users and Items Using Reviews for Recommendation," in Proc. of WSDM, 2017, pp. 425–434.

R. Burke, "Hybrid Recommender Systems: Survey and Experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331–370, Nov. 2002.

S. Jindal and B. Liu, "Opinion Spam and Analysis," in Proc. of WSDM, 2008, pp. 219–230.

H. Wang, N. Wang, and D. Yeung, "Collaborative Deep Learning for Recommender Systems," in Proc. of KDD, 2015, pp. 1235–1244.

M. B. Shaik and Y. N. Rao, "Secret Elliptic Curve-Based Bidirectional Gated Unit Assisted Residual Network for Enabling Secure IoT Data Transmission and Classification Using Blockchain," IEEE Access, vol. 12, pp. 174424-174440, 2024, doi: 10.1109/ACCESS.2024.3501357.

S. M. Basha and Y. N. Rao, "A Review on Secure Data Transmission and Classification of IoT Data Using Blockchain-Assisted Deep Learning Models," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 311-314, doi: 10.1109/ICACCS60874.2024.10717253.

Y. Chen, L. Wu, and M. S. Shang, "A Survey of Collaborative Filtering-Based Recommender Systems: From Traditional Methods to Hybrid Methods Based on Social Networks," IEEE Access, vol. 6, pp. 64301–64320, 2018.

H. Zhang et al., "Sentiment-Aware Recommender Systems: A Survey and Comparative Analysis," ACM Computing Surveys (CSUR), vol. 53, no. 5, pp. 1–35, Sep. 2020.

Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.

Reddy, B. V., Sk, K. B., Polanki, K., Vellela, S. S., Dalavai, L., Vuyyuru, L. R., & Kumar, K. K. (2024, February). Smarter Way to Monitor and Detect Intrusions in Cloud Infrastructure using Sensor-Driven Edge Computing. In 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) (Vol. 5, pp. 918-922). IEEE.

Sk, K. B., & Thirupurasundari, D. R. (2025, January). Patient Monitoring based on ICU Records using Hybrid TCN-LSTM Model. In 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) (pp. 1800-1805). IEEE.

Dalavai, L., Purimetla, N. M., Vellela, S. S., SyamsundaraRao, T., Vuyyuru, L. R., & Kumar, K. K. (2024, December). Improving Deep Learning-Based Image Classification Through Noise Reduction and Feature Enhancement. In 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA) (pp. 1-7). IEEE.

Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-Peer Networking and Applications, 16(6), 2714-2731.

Haritha, K., Vellela, S. S., Vuyyuru, L. R., Malathi, N., & Dalavai, L. (2024, December). Distributed Blockchain-SDN Models for Robust Data Security in Cloud-Integrated IoT Networks. In 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 623-629). IEEE.

Vullam, N., Roja, D., Rao, N., Vellela, S. S., Vuyyuru, L. R., & Kumar, K. K. (2023, December). An Enhancing Network Security: A Stacked Ensemble Intrusion Detection System for Effective Threat Mitigation. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1314-1321). IEEE.

Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 408-414). IEEE.

Praveen, S. P., Nakka, R., Chokka, A., Thatha, V. N., Vellela, S. S., & Sirisha, U. (2023). A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 2023.

Vellela, S. S., & Krishna, A. M. (2020). On Board Artificial Intelligence With Service Aggregation for Edge Computing in Industrial Applications. Journal of Critical Reviews, 7(07).

Reddy, N. V. R. S., Chitteti, C., Yesupadam, S., Desanamukula, V. S., Vellela, S. S., & Bommagani, N. J. (2023). Enhanced speckle noise reduction in breast cancer ultrasound imagery using a hybrid deep learning model. Ingénierie des Systèmes d'Information, 28(4), 1063-1071.

Vellela, S. S., Balamanigandan, R., & Praveen, S. P. (2022). Strategic Survey on Security and Privacy Methods of Cloud Computing Environment. Journal of Next Generation Technology, 2(1).

Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2024). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 1-11.

Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.

Vuyyuru, L. R., Purimetla, N. R., Reddy, K. Y., Vellela, S. S., Basha, S. K., & Vatambeti, R. (2025). Advancing automated street crime detection: a drone-based system integrating CNN models and enhanced feature selection techniques. International Journal of Machine Learning and Cybernetics, 16(2), 959-981.

Vellela, S. S., Roja, D., Sowjanya, C., SK, K. B., Dalavai, L., & Kumar, K. K. (2023, September). Multi-Class Skin Diseases Classification with Color and Texture Features Using Convolution Neural Network. In 2023 6th International

Conference on Contemporary Computing and Informatics (IC3I) (Vol. 6, pp. 1682-1687). IEEE.

Praveen, S. P., Vellela, S. S., & Balamanigandan, R. (2024). SmartIris ML: harnessing machine learning for enhanced multi-biometric authentication. Journal of Next Generation Technology (ISSN: 2583-021X), 4(1).

Sai Srinivas Vellela & R. Balamanigandan (2025). Designing a Dynamic News App Using Python. International Journal for Modern Trends in Science and Technology, 11(03), 429-436. https://doi.org/10.5281/zenodo.15175402

Basha, S. K., Purimetla, N. R., Roja, D., Vullam, N., Dalavai, L., & Vellela, S. S. (2023, December). A Cloud-based Auto-Scaling System for Virtual Resources to Back Ubiquitous, Mobile, Real-Time Healthcare Applications. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1223-1230). IEEE.

Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.