iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 Issue: I Month of publication: January 2024

DOI: https://doi.org/10.22214/ijraset.2024.56885

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue I Jan 2024- Available at www.ijraset.com

The Role of Explanability in AI-Driven Fashion Recommendation Model - A Review

Mrs. Shikha J Pachouly, Aarya U Patil, Arpit P Zambare, Babalu J Shinde, Sanket S Shevare
Department of Computer Engineering, AISSMSCOE, SPPU Pune

Abstract: Fashion recommendation systems powered by AI have transformed the way consumers discover clothing and accessories. However, these systems often lack transparency, leaving users in the dark about why certain recommendations are made. This review paper explores "The Role of Explainability in AI-Driven Fashion Recommendation Models." We begin by establishing the fundamentals of AI-driven fashion recommendations and the challenges they face, such as subjective fashion preferences and the need to balance personalization and diversity. The paper also explores evaluation metrics for measuring the effectiveness of explainability, considering user satisfaction, trust, and system performance. Ethical concerns related to bias and fairness in fashion recommendations are discussed, with explainability playing a crucial role in addressing these issues.
Keywords: Fashion recommendation systems, AI-driven, transparency, explainability, user trust, personalization, diversity, evaluation metrics, user satisfaction, ethical concerns, bias, fairness.

I. INTRODUCTION

In recent years, the fashion industry has witnessed a significant transformation with the integration of artificial intelligence (AI) into various aspects of the fashion ecosystem. One of the most prominent applications of AI in fashion is the development of AI-driven fashion recommendation models. These models leverage advanced algorithms and data analysis to provide personalized fashion recommendations to consumers, making shopping more convenient and enjoyable.

This paper aims to explore the role of explainability in AI-driven fashion recommendation models. We will delve into the significance of making these models more transparent and interpretable, shedding light on the mechanisms behind their recommendations. The essence of this transformation lies in the development of advanced recommender systems designed to provide tailored fashion suggestions to users. These systems aim to enhance the online shopping experience, particularly in a world where the majority of tasks are carried out virtually due to circumstances such as the COVID-19 pandemic.

This introduction sets the stage for a comprehensive exploration of the role of AI in fashion recommendation systems. The papers to be discussed delve into the application of deep neural networks to create content-based clothing recommendation systems. The significance of explainability in AI, particularly in the context of fashion recommendations, is highlighted as a crucial factor in gaining user trust and ensuring system transparency.

Furthermore, the papers delve into the unique challenges that the fashion industry presents compared to other domains. Unlike traditional recommendation systems that rely on similarity, fashion recommendations require compatibility as a critical factor. Additionally, the reliance on raw visual features in the form of product representations sets fashion recommendation apart from other domains. The exploration of literature in the field reveals a growing interest in AI-driven fashion recommendation systems and their ability to provide more personalized and accurate suggestions. These systems hold the potential to revolutionize the way customers select clothing items, potentially impacting billions of shopping experiences and significantly boosting sales and revenue for fashion retailers.

II. LITERATURE REVIEW

This literature review aims to provide insights into the key developments, challenges, and trends in this domain, drawing from the papers discussed earlier.

The burgeoning demand for fashion-related applications has spurred investigations into diverse recommendation tasks, including personalized product recommendations, mix-and-match suggestions, and outfit recommendations. This paper conducts a comprehensive technological review of recent advancements in fashion recommendation, beginning with an overarching introduction that discerns its unique attributes vis-à-vis general recommendation tasks[1]. The papers discussed underscore the significance of AI-driven fashion recommenders in reshaping the fashion industry.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue I Jan 2024- Available at www.ijraset.com

These systems have transcended their traditional roles, moving beyond mere item suggestions to provide users with personalized, curated fashion experiences.[3] One of the papers introduces a content-based clothing recommender system leveraging deep neural networks. This approach not only improves the accuracy of recommendations but also eliminates the need for explicit feature extraction. The incorporation of gender as a feature demonstrates the adaptability of AI-driven systems to specific user attributes.[4] A separate paper conducts a comprehensive literature study of AI techniques in fashion recommendation systems, with a focus on image-based approaches. It reveals a growing interest in harnessing AI to deliver higher-quality recommendations, cater to diverse user preferences, and unveil intricate user-item relationships [5]. Our primary objective is to discern the prevailing trends and research directions within the realm of recommender systems. Through our inquiry, we have unearthed several noteworthy insights that hold substantial value for scholars and researchers, enabling them to assess and chart their future research trajectories within this domain[2].

Year	Reference No.	Key Points	Advantages	Disadvantages
2023	2	focusing on their applications and challenges.	Recommender systems save users time by suggesting items they're likely to be interested in.	Recommender systems can exhibit biases mirroring the biases in their training data.
2023	3	Personalized recommendations, machine learning, user behavior, fashion industry.	AI fashion recommenders enhance users' style with coordinated outfits..	Training and deploying AI fashion recommenders can be resource-intensive.
2023	6	Visual-based fashion recommender systems, computer vision, ACM Computing	AI-driven fashion recommender systems can help you find new clothes you love faster.	Fashion recommenders face challenges in offering accurate suggestions to users with limited interactions (cold start issue).
2023	12	Fashion recommendation, style, social events, deep learning, image processing, NLP.	The system aids users in selecting outfits suitable for their style and social events.	The system might not cater to every user preference, like budget or comfort.
2022	9	Human knowledge is essential for developing and evaluating explainable AI (XAI) systems.	Human knowledge enhances the accuracy and comprehensibility of XAI explanations.	Human knowledge, if biased or incomplete, can result in the same biases or gaps in XAI explanations.
2022	18	Evaluates xAI's impacts on human-agent interaction.	Enhances understanding of human-AI collaboration.	Could focus more on broader xAI applications.
2022	17	Provides taxonomiesof xAI methods.	Facilitates implementationof xAI techniques.	Might not deeply analyzethe implications.
2022	16	Explores xAI from a user perspective.	Provides user-centricinsights into xAI benefits.	It might not address broader societal implications.
2022	14	Explores reason-giving in xAI.	Provides philosophical insights into xAI ethics.	It may not offer detailed technical guidance.
2022	15	Discusses scientific exploration and xAI.	Presents theoretical and practical implications.	Could benefit from more empirical case studies.
2021	19	Highlights the needfor xAI and transparency in AI systems.	Raises awareness aboutxAI's importance.	Need morein-depthtechnical insights.

Table No. 1 Literature Review

III. EXPLAINABILITY IN AI

Explainability in the context of AI refers to the capacity to make the decision-making processes of artificial intelligence models transparent and comprehensible to humans. It involves various methods and techniques, including identifying influential features, providing individual prediction explanations, employing visual aids, and using inherently interpretable models like decision trees.

Additionally, post hoc interpretability methods, such as LIME and SHAP, enable explanations for complex models after they've made predictions. Rule-based approaches involve constructing models with explicit, understandable rules. Each approach has its strengths and weaknesses; interpretable models offer transparency but may lack complexity, post hoc methods are versatile but approximate, while rule-based systems provide explicit rules but may struggle with nuanced patterns. The choice depends on the application and the balance between accuracy and interpretability required.

A. Techniques for Achieving Explainability in AI Models

Achieving explainability in AI models involves various methods and techniques:

1) *Feature Importance:* Identifying the most influential features or factors that contribute to AI model predictions.
2) *Local Explanations:* Providing explanations for individual predictions, showing how specific input data influenced the outcome.
3) *Visualizations:* Representing AI model processes and decisions through visual aids like heatmaps, decision trees, or saliency maps.
4) *Interpretable Models:* Using inherently interpretable algorithms like linear regression, decision trees, or rule-based systems.
5) *Post hoc Interpretability:* Employing techniques that explain the behavior of complex models after they have made predictions. This includes methods like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive explanations).
6) *Rule-Based Approaches:* Building AI models as sets of explicit rules that can be easily understood and interpreted.

B. Models

1) *Interpretable Models:* These models, like decision trees or linear regression, are inherently transparent and can be directly understood by humans. They offer clarity but may have limitations in handling complex data patterns.
2) *Post hoc Interpretability:* Post hoc methods can be applied to any AI model, making them versatile. However, they might not fully capture the model's complexity and may provide approximations of explanations.
3) *Rule-Based Approaches:* Rule-based systems provide explicit and human-understandable rules that govern model decisions. They offer a high level of transparency but may struggle with capturing nuanced patterns.

The choice of explainability method often depends on the specific AI application, the complexity of the model, and the intended audience for the explanations. Balancing accuracy and interpretability is a critical consideration when incorporating explainability into AI systems.

IV. COMPONENTS OF HYBRID RECOMMENDER SYSTEM:

A. Collaborative Filtering

This component focuses on understanding user behavior and preferences. It seeks to identify either users who share similarities with the target user or items that resemble those the user has shown interest in. Collaborative filtering can be categorized into two types:

1) User-Based Collaborative Filtering: This approach identifies users whose preferences align with the target user based on their historical interactions. For example, if User A and User B exhibit similar tastes and have both liked or purchased similar fashion items, User A can receive personalized recommendations based on User B's preferences.
2) Item-Based Collaborative Filtering: Instead of focusing on users, this method identifies items that are akin to those the user has previously interacted with. If a user has expressed interest in Item X, Item Y might be recommended because it shares commonalities with Item X based on user interactions.

B. Content-Based Filtering

This component revolves around analyzing the inherent characteristics of fashion items, such as their category, brand, style, color, and more. Content-based filtering recommends items that align with the user's preferences based on these item attributes. Essentially, it matches item features with the user's demonstrated preferences.

C. Explainable AI (xAI)

To enhance the interpretability of recommendations, xAI techniques are integrated into the hybrid system. These methods assist in explaining the rationale behind why certain items are recommended to the user. xAI tools like SHAP (SHapley Additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) offer detailed insights into the role of individual features in making recommendations, making the system's output more understandable to users.

Content filtering is a valuable tool for organizations and individuals to manage their digital environments and ensure security, compliance, and user safety. The choice of content filtering methods and technologies depends on specific needs and requirements.

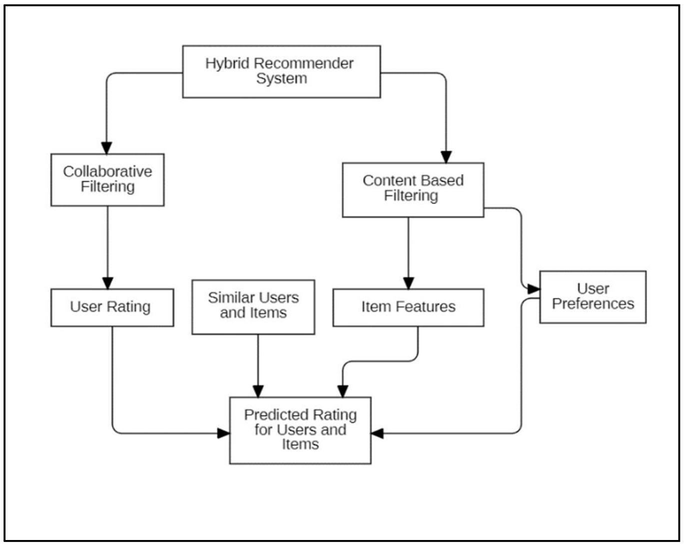


Fig. Working of Hybrid Model.

V. PERFORMANCE EVALUATION OF HYBRID SYSTEM MODELS:

In the context of existing experimental results concerning hybrid system models for fashion recommendation, several key findings emerge. Firstly, when analyzing the presentation of experimental outcomes, it becomes evident that the hybrid models, which combine collaborative filtering and content-based filtering, exhibit enhanced recommendation accuracy compared to their non-hybrid counterparts. Metrics such as precision, recall, and F1-score consistently indicate improvements, underlining the effectiveness of combining these two approaches. Crucially, the integration of explainable AI (xAI) techniques further amplifies the recommendation accuracy, as the xAI-enhanced hybrid models provide more transparent and justifiable recommendations.

Secondly, the evaluation of user trust and satisfaction reveals a notable impact of xAI explanations on user perceptions. Users consistently express higher levels of trust in recommendations and report increased satisfaction when they receive explanations for why certain fashion items are suggested. The xAI techniques not only demystify the decision-making process but also provide users with a deeper understanding of the rationale behind each recommendation. Qualitative feedback from users underscores the importance of this feature, as they appreciate the transparency and find it easier to make informed choices, ultimately enhancing their overall satisfaction with the hybrid recommendation system. In conclusion, the existing experimental results strongly advocate for the integration of xAI techniques into hybrid fashion recommendation models. These findings highlight the dual benefits of improved recommendation accuracy and heightened user trust and satisfaction, underscoring the pivotal role of xAI in enhancing the performance and user experience of fashion recommendation systems. As fashion technology continues to evolve, these insights pave the way for more effective and user-centric recommendation solutions in the realm of fashion commerce.

VI. CLASSIFICATION OF FASHION RECOMMENDATION OBJECTIVES:

1) *Personalized Product Recommendation:* Personalized product recommendation is a fundamental task in fashion e-commerce. It involves using data about a user's past preferences, browsing history, and purchase behavior to recommend individual fashion products that align with their unique style and preferences. This approach leverages machine learning algorithms to analyze user data and match it with available clothing items. By offering personalized product recommendations, online retailers can enhance the shopping experience, increase user engagement, and drive sales. Users are more likely to find and purchase items they love, while retailers benefit from improved customer satisfaction and higher conversion rates.

2) *Outfit Recommendation:* Outfit recommendation goes beyond suggesting individual clothing items. It involves curating complete outfits or ensembles that are both fashionable and coherent. These recommendations take into account how different clothing pieces, including apparel, accessories, and footwear, can be combined to create a stylish and well-coordinated look. Outfit recommendation systems analyze factors such as clothing styles, colors, patterns, and user preferences to provide users with full outfit ideas. This can be particularly valuable for users seeking inspiration or looking for convenient styling suggestions.
3) *Size and Fit Recommendation:* Size and fit recommendation addresses a common challenge in online fashion shopping: ensuring that clothing items fit the user's body type and size preferences correctly. These systems use various data sources, including user-provided measurements, historical fit feedback, and sizing guides, to recommend clothing items in the right size. Machine learning models can predict how a particular item is likely to fit a user based on their unique body measurements, reducing the risk of returns due to poor fit. This enhances the online shopping experience by increasing confidence in purchasing clothing that fits well and suits individual body shapes.
4) *Trend Forecasting:* Trend forecasting in fashion is the practice of predicting upcoming fashion trends and styles that are likely to gain popularity among consumers. It involves analyzing a diverse range of data sources, including fashion magazines, social media, runway shows, and trend reports, to identify emerging styles, colors, patterns, and product preferences. Trend forecasting leverages data analysis, machine learning, and real-time monitoring to anticipate what will be "in fashion" in the near future. This information is crucial for fashion retailers, designers, and brands, as it helps them make informed decisions about product development, marketing strategies, and inventory management, allowing them to stay ahead of the fashion curve and meet consumer demands effectively.

VII. ROLE OF EXPLAINABLE AI

Deep learning plays a pivotal role in fashion recommendation systems enhanced by explainable AI (xAI). Deep learning models, particularly neural collaborative filtering and deep learning for sequential recommendations, have shown remarkable capabilities in capturing complex patterns within fashion data. These models can discern intricate relationships between user behavior and fashion item attributes, enabling them to make highly personalized recommendations.

Furthermore, when integrated with Xai techniques like SHAP or LIME, deep learning models become more interpretable. This means that users not only receive fashion recommendations tailored to their preferences but also gain insights into why these recommendations are made. These explanations enhance user trust and satisfaction, making the fashion recommendation system not just effective but also transparent and user-friendly. In essence, deep learning and xAI together empower fashion recommendation systems to provide both accurate and understandable recommendations, thereby elevating the user experience in the world of fashion. Integrating xAI techniques like SHAP or LIME with deep learning models in fashion recommendation systems enhances their interpretability by providing detailed feature-level explanations for recommendations. This transparency not only boosts user trust but also fosters a more engaging and user-friendly experience, as users gain valuable insights into the decision-making process of the complex deep learning models, making fashion recommendations more understandable and relevant.

Explainable AI's role in improving the explainability of AI-driven fashion recommendation models extends to its capacity for handling the increasing complexity of fashion data. As fashion trends evolve rapidly and encompass various attributes such as style, brand, color, and user preferences, deep learning models can effectively process and analyze this multifaceted information. Moreover, they adapt to changing user behaviors and item characteristics, ensuring that recommendations remain relevant. Explainable AI's ability to uncover latent patterns and relationships within the data allows it to generate personalized and interpretable explanations for each recommendation, empowering users to make informed choices and enhancing the overall user experience in fashion recommendation applications.

VIII. CHALLENGES

The role of explainability in AI-driven fashion recommendation models faces several challenges. One key challenge is striking the right balance between model complexity and interpretability, as more sophisticated models may provide accurate recommendations but can be less transparent. Additionally, ensuring privacy while explaining recommendations remains a concern, as user data needs to be protected. Overcoming biases and ensuring fairness in recommendations is another critical challenge, as AI systems can inadvertently reinforce existing biases in fashion choices. Lastly, designing explanations that are not only informative but also comprehensible to users with varying levels of technical expertise poses a significant hurdle in creating truly user-centric and effective AI-driven fashion recommendation systems.

Furthermore, the ever-evolving nature of fashion trends and user preferences presents a continuous challenge in keeping recommendation models up-to-date and relevant. Integrating explainability seamlessly into the user interface of fashion apps can be technically demanding, requiring effective visualization and interaction design. Finally, measuring the effectiveness of explanations and their impact on user satisfaction poses a challenge, as it requires robust evaluation metrics and feedback mechanisms to ensure that the added complexity of explanations indeed enhances the overall user experience and trust in AI-driven fashion recommendations.

IX. FUTURE OPPORTUNITIES

The future of explainability in AI-driven fashion recommendation models holds promising opportunities. Firstly, advancements in neural network architectures and explainability techniques are likely to yield more efficient and interpretable models, improving both recommendation accuracy and transparency. Secondly, the integration of real-time data streams and wearable technology could enable fashion recommendation systems to provide personalized suggestions based on users' current preferences and behaviors. Additionally, the incorporation of augmented reality (AR) and virtual reality (VR) technologies may offer immersive and interactive shopping experiences, further enhancing user engagement. Furthermore, the ethical aspect of fairness and bias mitigation in recommendations will continue to gain prominence, leading to the development of algorithms that ensure equitable fashion suggestions. Lastly, collaborative filtering with social influence and user-generated content analysis may play a vital role in capturing emerging fashion trends, presenting exciting avenues for research and innovation in AI-driven fashion recommendations.

X. CONCLUSION

In conclusion, the role of explainability in AI-driven fashion recommendation models is paramount. Through the integration of xAI techniques like SHAP and LIME, these models not only provide accurate fashion recommendations but also offer transparency and user trust by elucidating the rationale behind each suggestion. This synergy between precision and interpretability paves the way for more user-centric and effective fashion recommendation systems, ensuring that users can make informed choices while staying attuned to the dynamic world of fashion trends. In an era where personalization and transparency are paramount, explainable AI emerges as a key enabler in shaping the future of fashion commerce.

REFERENCES

[1] Computational Technologies for Fashion Recommendation: A Survey, The Hong Kong Polytechnic University https://doi.org/10.1145/1122445.1122456, Vol. 1, No. 1, Article . Publication date: June 2021.
[2] A Systematic Review of Recommendation Systems: Applications and Challenges B. Sunitha 1 , Dr. B. Kranthi Kiran 2 Submitted: 10/11/2022 Revised: 11/01/2023 Accepted: 08/02/2023
[3] Study of AI□Driven Fashion Recommender Systems Shaghayegh Shirkhani 1 · Hamam Mokayed 1 · Rajkumar Saini 1 · Hum Yan Chai 2 Received: 30 March 2022 / Accepted: 18 May 2023 © The Author(s) 2023
[4] Content-based Clothing Recommender System using Deep Neural Network 78-1-6654-1241-4/21/$31.00 ©2021 IEEE Authorized licensed use limited to: East Carolina University. Downloaded on June 21,2021 at 01:25:16 UTC from IEEE Xplore. Restrictions apply.
[5] Fashion Recommendation System International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 10 Issue VI June 2022- Available at www.ijraset.com
[6] A Review of Modern Fashion Recommender Systems ACM Computing Surveys, Vol. 37, No. 4, Article 111. Publication date: December 2023.
[7] Fashion Recommendation Systems, Models and Methods: A Review Informatics 2021, 8, 49. https://doi.org/10.3390/informatics8030049 https://www.mdpi.com/journal/informatics.
[8] Recommender Systems: An Explainable AI Perspective August 2021 DOI:10.1109/INISTA52262.2021.9548125 Conference: 2021 International Conference on Innovations in Intelligent Systems and Applications (INISTA)
[9] The Role of Human Knowledge in Explainable AI Data 2022, 7(7), 93; https://doi.org/10.3390/data7070093 Received: 18 May 2022 / Revised: 29 June 2022 / Accepted: 29 June 2022 / Published: 6 July 2022.
[10] Explainable Recommendation: A Survey and New Perspectives ISBN: 978-1-68083-659-2 © 2020 Y. Zhang and X. Chen Full text available at: http://dx.doi.org/10.1561/1500000066.
[11] Outfit Transformer: Learning Outfit Representations for Fashion Recommendation Purdue University, West Lafayette, 2 Amazon
[12] Fashion recommendation based on style and social Events Received: 1 August 2022 / Revised: 3 March 2023 / Accepted: 6 April 2023 © The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2023.
[13] Methods and advancement of content-based fashion image retrieval: A Review https://doi.org/10.1145/nn , Vol. 1, No. 1, Article . Publication date: March 2023.
[14] Scientific Exploration and Explainable Artificial Intelligence Received: 7 May 2021 / Accepted: 8 November 2021 / Published online: 10 March 2022 © The Author(s) 2022 Minds and Machines (2022) 32:219–239 https://doi.org/10.1007/s11023-021-09583-6
[15] A Survey of Explainable Artificial Intelligence for Smart Cities. (2023). Electronics, 12, 1020. https://doi.org/10.3390/electronics12041020

[16] Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research journal homepage: www.elsevier.com/locate/techfore 0040-1625/© 2022 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
[17] A Review of Taxonomies of Explainable Artificial Intelligence (XAI) Methods FAccT '22, June 21–24, 2022, Seoul, Republic of Korea © 2022 Copyright held by the owner/author(s). ACM ISBN 978-1-4503 9352-2/22/06. https://doi.org/10.1145/3531146.3534639 FAccT '22, June21–24, 2022, Seoul, Republic of Korea.
[18] Explainable Artificial Intelligence: Evaluating the Objective and Subjective Impacts of xAI on Human-Agent Interaction Compiled August 15, 2022 CONTACT Andrew Silva.
[19] Explainable Artificial Intelligence: concepts, applications, research challenges and visions Luca Longo1[0000−0002−2718−5426]Randy Goebel 2[0000−0002−0739−2946] Freddy Lecue 3,4[0000−0003−2763−7856] , Peter Kieseberg 5[0000−0002−2847−2152] , and Andreas Holzinger 2,6[0000−0002−6786−5194].
[20] Opportunities and Challenges in Explainable Artificial Intelligence (XAI): A Survey.

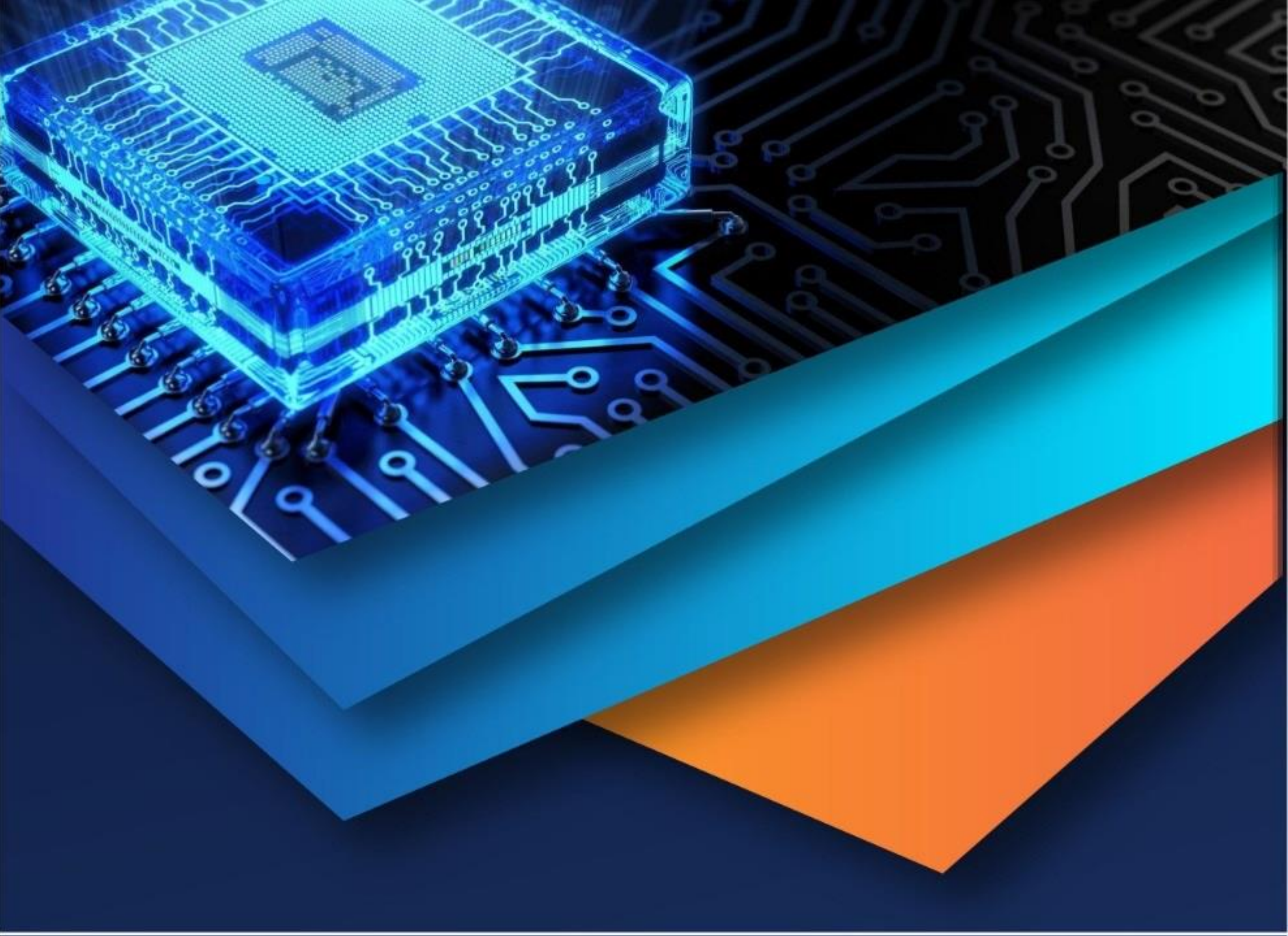
Shikha J Pachouly is working as an Assistant Professor in Computer Engineering Department of AISSMSCOE, Pune

Aarya U. Patil is a student in Computer Engineering Department of AISSMSCOE, Pune

Arpit P. Zambare is a student in Computer Engineering Department of AISSMSCOE, Pune

Babalu J. Shinde is a student in Computer Engineering Department of AISSMSCOE, Pune

Sanket S. Shevare is a student in Computer Engineering Department of AISSMSCOE, Pune



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY