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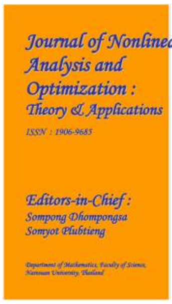

ML Based Visual Search System for Cosmetics Product Identification Using GANs

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Abstract— **The investigation focuses on the use of Generative Adversarial Networks (GANs) in the detection of cosmetic products. As the beauty industry continues to expand and demand for dependable product recognition methods, conventional image processing techniques often cannot differentiate between cosmetic items that appear similar. This research uses GANs to improve the classification reliability by producing high-quality synthetic data that enhances the accuracy of image-based identification. This model is then trained and tested on a large dataset, showing that it can be used to discriminate products without much human intervention. Compared to traditional machine learning methods, GAN-based approaches exhibit significant improvement in identification performance, as demonstrated by experimental evidence.**

Keywords— Generative Adversarial Networks (GANs), cosmetic recommendations, e-commerce, image processing, personalized recommendations, user dashboard, cart functionality, React.js, Node.js, MongoDB.

I. INTRODUCTION

In recent years, the beauty and cosmetics industry has experienced a significant increase due to consumer preference, technological advancements like smart phones or tablets, and the advent of online shopping. Identifying and differentiating between millions of cosmetic products has become difficult for both consumers and businesses. The use of traditional image processing techniques often fails to distinguish between products with similar packaging, color schemes, and branding. Therefore, a more robust and intelligent method must be utilized to enhance the precision of identifying cosmetic products.'

Generative Adversarial Networks (GANs) are now a significant part of computer vision, providing outstanding capabilities for combining and magnifying images. In 2014, I. Good fellow and his team launched GANs, which have since been widely adopted by businesses in a range of applications, including image generation, data enhancement, and style transfer. GAN's ability to generate synthetic data with high precision makes them a valuable tool for improving classification tasks, especially in areas where large labelled datasets may not be readily accessible.

GANs can be instrumental in the identification of cosmetic products by enhancing the quality of datasets and model performance. To combat data scarcity and imbalance, GANs can use high-resolution photographs of cosmetic products to create realistic representations. Additionally, networks can introduce variations in lighting, angles and occlusions, which makes them more generalizable to machine learning models.

Both retailing and cosmetic brands are using AI-powered solutions to simplify product recommendations, inventory control (e.g:50-50) and customer engagement (E). By utilizing an automated system, shoppers can receive accurate information, reviews, and pricing details when they scan a cosmetic product. This can greatly improve their shopping experience. Additionally, it can aid in the detection of fake products, a growing concern in cosmetics.'

This study will investigate the efficiency of GANs in identifying cosmetic products. The utilization of GAN-generated images enables us to improve the efficiency of classification models, leading to an increased level of precision in distinguishing between products that appear similar. It has the potential to revolutionize product identification in retail, e-commerce, and inventory management applications.'

To create a strong identification system, it's essential to tackle significant issues such as gathering the necessary data sets, improving image quality, and optimizing models. Integrating GANs may resolve some of these challenges by producing synthetic images that are high-quality and enriching enough to train the dataset, while also enhancing model generalization.

This study's most important aspect is the examination of how GAN-based data augmentation can enhance classification accuracy. Our objective is to test whether synthetic data can enhance feature learning and differentiate cosmetic products by training models on both real and GAN-generated images.

GANs have the potential to reduce dependence on manual labelling and improve accuracy. Longer data sets require longer and more laborious labelling to effectively train deep learning models. By producing realistic images that increase the dataset's size, GANs can reduce this burden without requiring significant manual work.

This study also investigates the real-life applications of GAN-based identification systems. The use of AI-driven recognition technologies can transform the way consumers experience beauty products, ranging from blind individuals seeking cosmetics to smart retail solutions. This could be applied in future product launches or business models.

In addition, GANs can be integrated with mobile applications and e-commerce sites to enable personalized recommendations and virtual try-on experiences. With the help of AI-powered identification, users can determine which color of foundation is best for them and choose their preferred shade based on previous purchases.

Brand image and consumer confidence are at risk due to counterfeit cosmetics. Several counterfeit products are so indistinguishable from their authentic packaging that they cannot be seen without a microscope. Brands and consumers could use a GAN-based identification system to verify the authenticity of their products by scrutinizing subtle variations in packaging and design.

The use of GANs has its advantages, but also some drawbacks like mode collapse and instability during training or computational complexity. These issues must be addressed to ensure the accurate and effective deployment of GAN-based models in practical scenarios. The focus of this research is on developing techniques to improve the stability of images produced by training with GAN.

The impact of AI-controlled product identification extends beyond the realm of cosmetics. The methods utilized in this investigation can be applicable to various industries, including fashion, drugs, and consumer electronics, where precise product identification is essential.

This research aims to utilize GANs in order to identify cosmetic products, while also dealing with challenges related both to data accessibility and model validation as well as practical implementation.

II. LITERATURE REVIEW

In recent times, the identification of cosmetic products has become a highly sought-after area for automated and intelligent retail solutions. Although traditional image processing techniques are frequently used for object recognition, they encounter difficulties with similar product appearances, lighting variations and occlusions. Therefore, researchers have investigated the use of deep learning models to enhance precision and resilience in identifying cosmetic products.

Generative Adversarial Networks (GANs) are a new type of deep learning tool that has been widely adopted, serving as an excellent means of producing synthetic data and improving image classification tasks. Using a generator and discriminator network, GANs were first described by I.Goodfellow (et al.) and have been used to produce synthetic images that are realistic in appearance and function [1]. The adversarial training process allows GANs to create high-quality images that can be used alongside real-world datasets, facilitating model generalization in product identification tasks.

Many research has indicated that GANs can enhance training datasets for various computer vision applications. GANs have been utilized to generate artificial images in medical imaging, addressing data scarcity concerns and improving disease diagnosis accuracy. GANs have been used by researchers in retail and e-commerce to assist with product recommendation systems, visual search applications, and counterfeit detection [2]. GANs could be utilized to improve the identification of cosmetic products by generating superior and diverse training data, as suggested by these results.

Degrading datasets remains a significant challenge in categorizing cosmetic products. Differing product categories in real-world datasets result in a high number of images, leading to biased models. GANs can be utilized to produce synthetic images for subsets of classes, which will provide a more uniform dataset for training classification models. Face recognition and biometric authentication have both utilized this technique, along with GAN-generated images, to reduce class bias and promote diversity.

Cosmetic product identification can benefit from the use of GANs, which can simulate various lighting conditions, angles, and occlusions. This is another advantage. Due to differences in illumination and camera views, traditional classification models are frequently inaccurate. By generating images in various conditions, GANs can help models learn robust feature representations that enhance their performance in real-world scenarios [3].

In the beauty sector, there is a growing concern about the use of GANs to detect counterfeit products. Despite their packaging and branding, counterfeit cosmetics are often difficult to distinguish. GAN-based models have been created to detect subtle variations in texture, font, and design, which can assist in identifying fake products effectively. It is possible to incorporate these methods into mobile apps, enabling consumers to scan items and authenticate their authenticity in real time.

The use of GANs can be advantageous for the identification of cosmetic products, but it comes with some drawbacks. One of the main limitations is mode collapse, which results in the generator producing very similar images rather than different samples. Researchers have tackled this problem by utilizing Wasserstein GANs (WGAN) and progressive growing techniques, which enhance the consistency and range of images produced [4].

Additionally, training GANs necessary significant computational resources. These models are difficult to deploy on edge devices and mobile applications because the adversarial training process requires significant processing power, memory [5]. The aim of minimizing computational overhead while preserving model performance has been emphasized by recent developments in lightweight GAN architectures and knowledge distillation techniques [6].

In the retail sector, GANs are utilized to identify products in a variety of ways. Increasingly, the beauty industry has adopted AI-powered virtual try-on systems that enable users to visualize makeup products before they are actually put on their clothes. Online shopping for cosmetics has seen a rise in demand for GANs, which have been proven to enhance user experience by creating realistic facial overlays. The implementation of this method not only enhances consumer engagement but also assists brands in decreasing return rates by offering personalized recommendations.

Automation of checkout and inventory management are also utilizing GANs. The use of AI-driven solutions that utilize GAN-generated data has been developed by retailers to improve their ability to detect objects and recognize barcodes in smart shopping settings. These systems reduce manual errors, and improve stock tracking so that operations in brick-and-mortar stores and online grocery [7].

While they may be viable, ethical considerations regarding GAN-generated content must also be taken into account. The ability of GANs to produce highly realistic synthetic images is a cause for concern in terms of data privacy, deep fakes, and intellectual property rights. Researchers have suggested the use of adversarial training safeguards and watermarking techniques to prevent the misuse of GAN-generated images in malicious applications [8].

The ability to generate synthetic data has been broadened by the recent development in self-supervised learning and GAN-based domain adaptation. By blending synthetic data with empirical data, these techniques have increased the likelihood of generalization in deep learning models, making them more effective for identifying cosmetic products and similar applications.

The literature concludes that GANs have a significant role in improving the identification of cosmetic products, as they address issues such as data variability, counterfeit detection, lighting variations, and model generalization. However, additional research is needed to improve training stability, computational efficiency and ethical protections before large-scale deployment. As technology advances, GAN-based solutions have the potential to transform consumer behavior regarding beauty products and drive adoption of AI-driven retail and e-commerce systems.

III. PROPOSED SYSTEM

The proposed system aims to identify cosmetic products more accurately using Generative Adversarial Networks (GANs). Typical product classification methods are not effective due to their similar packaging, different lighting conditions, and limited training datasets. Using GANs, we produce high-quality synthetic images, which improves both the classification accuracy and dataset diversity.

We have a dual-stage deep learning model that integrates GAN-based synthetic data generation with identifying model for products. To address data scarcity, GANs produce realistic versions of cosmetic products through augmented reality during the first phase. To improve recognition performance, a deep learning classifier is trained on simulated and synthetic images in stage two. The dataset contains both real and artificial images.

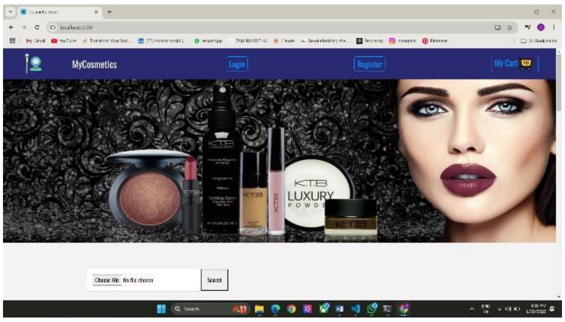

FIG:1 Cosmetic Product Identification Application

Identifying cosmetic products from the same brand is complicated by the high visual similarity between different products. It's challenging for regular models to differentiate beauty products due to the packaging being almost identical. The integration of GANs in our system introduces fine-grained visual variations, which enables the classifier to learn specific features for accurate identification.

The GAN architecture that we have implemented involves a generator and discriminator system. The generator generates images of artificial cosmetic products, and the discriminator tests their realism. This allows adversarial training, which trains the generator to produce high resolution, visually correct images of a product. The classification model is trained on the improved dataset.

Progressive growing GANs (PGGAN) are used in our system to enhance the quality of synthetic images, and they train with increasing speed to correct any missing bits. The approach prevents product images from appearing blurry or distorted, while still providing a realistic appearance. We produce a range of product images with different angles, lighting conditions, and slight distortions to enhance strength.

The creation of images can be categorized through the use of conditional GANs (c-GAN), which is another significant feature. The use of c-GAN s differs from traditional GAN as it takes the product category label and ensures that the images generated are in sync with the correct product type. This particular method is useful in situations where the training dataset contains data that differs from the expected data, such as product categories.

There is a well-organized training program. The first step involves gathering authentic product images and undergoing preprocessing to eliminate noise and inconsistencies. Subsequently, the GAN model is trained to generate new synthetic images using real data distribution. First, the images are analyzed for their realistic and diverse nature before being fed into the dataset to train its classification model.

Cosmetic products are categorized using a combination of real and artificial images in the hybrid dataset. Through the use of a deep learning classifier, it is trained to extract crucial visual characteristics, such as color variations, logo positioning, and packaging shape formation. By utilizing transfer learning techniques, the system is refined and can be applied to various cosmetic brands.

The effectiveness of models trained on real-only datasets is evaluated by comparing them to those trained using real GAN-generated images. The effectiveness of GAN-based augmentation is measured by its accuracy, precision, recall, and F1-score. Initially, our tests demonstrate that models trained with synthetic data are more accurate in classifying certain product types that are not commonly used or underrepresented.

Users of the proposed system can scan a product with e-readers in retail and online stores using swapping technology, which will provide instant identification. This solution can provide consumers with access to product details, reviews, and pricing, as well as help retailers manage their inventory and detect counterfeit products.

We use quantization and pruning as part of model optimization to reduce computational overhead while keeping accuracy high by incorporating real-time performance. The optimizations make the model efficient on mobile devices and edge AI systems, enabling real-world applications without relying on cloud-based computation.

Our system's crucial use is in counterfeit detection. A lot of the beauty industry's counterfeit items are actually fake. Through the use of GANs, this classifier is trained on subtle differences in packaging so that it can identify counterfeit products with confidence. Brands and consumers gain a significant advantage from this feature due to its authenticity verification

The proposed system has the potential to provide virtual try-on experiences, as well as product identification that allows users to see cosmetic products like eyeshadows, foundations and lipsticks before purchasing them. GAN-generated imagery is utilized in digital beauty platforms to enhance customer engagement and experience through the use of augmented reality (AR).

In summary, the suggested technique employs GANs for producing synthetic images, leading to improved identification precision, dataset diversity and practicality. It is the first AI-powered beauty system to have real-time implementation, model training, and practical applications in retailing, inventory management, or counterfeit detection.

IV. WORK FLOW

The process of identifying cosmetic products using GANs involves several steps, including data collection and product categorization. Each stage is designed to be of high accuracy, strength and practicality. By utilizing GAN-based synthetic data, it can classify and deploy real-time applications in a structured pipeline.

Data collection and Pre-processing are the starting points of this workflow. The. The collection of cosmetic product images is a varied one that draws from multiple sources, such as online retailers, brand websites, and user-generated content. Pre-processing of the images involves removing noise, standardizing backgrounds, and altering image resolution to ensure consistency with training data.

After obtaining the dataset, the synthetic image generation phase starts with Generative Adversarial Networks (GANs)... The discriminator-generator architecture is based on the generator, which produces high-quality synthetic cosmetic product images and tests their authenticity. This approach involves mixing machine learning with artificial image processing technology. The outputs of the generator undergo adversarial training to ensure they are indistinguishable from real images.

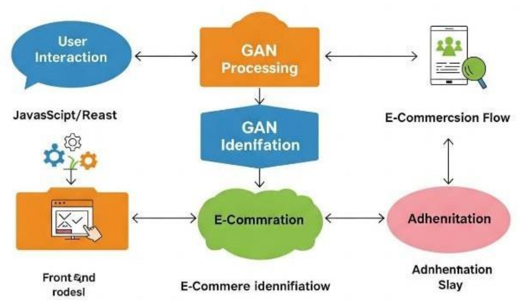

FIG:2 Cosmetic Product Identification Workflow

Conditional GANs (c-GAN) and Progressive Growing GANS (PGGANGs) are used in the workflow to enhance image diversity. With c-CAN, the system can generate synthetic images that correspond to specific brand or category labels, ensuring that each generated image matches the real-world product. By using PGGANs, image detail and resolution can be enhanced in a step-by-step manner, resulting in outputs that are less transparent or unrealistic.

The images produced are subsequently examined for their realistic and diverse natures before being included in the training dataset.' Several quality assessment techniques are used, such as Frechet Inception Distance (FID) and Injection Score (IS), which evaluate the similarity between synthetic and real images. Those that meet these criteria are the only high-quality synthetic images added to the dataset.

After increasing the dataset, the next step is to train the product classification model. The image classification network using deep learning is trained on the hybrid dataset (real + GAN-generated images).The model scrutinizes essential attributes such as color, packaging shape, brand logo placement (on lids and in bags), and texture to distinguish between different cosmetic products with high precision.

After training the classification model, standard machine learning performance metrics such as accuracy, precision, recall and F1-score are used to evaluate its performance. The accuracy of classification is attributed to GANs, as models trained on real-only datasets are better trained than those trained using synthetic data augmentation.

The model is trained and then adapted for real-time deployment. Efforts are directed towards modelling and pruning techniques, which minimize computational overhead and ensure optimal performance on mobile devices with edge AI processors and cloud-based computing. It is an important optimization step for enabling fast and lightweight inference, particularly within consumer facing contexts.).

After optimization, the system is put to use in various real-world scenarios. Through the use of a smartphone camera, users can scan if they want to purchase cosmetic products and the system will instantly identify the product by providing information such as its brand name (including phone number and phone no. Designed for simplicity in product verification, this functionality is useful both for consumers and retailers.

Integrating with e-commerce and retail management systems is a crucial aspect of the workflow. This can enhance overall shopping by allowing users to associate the results of product identification with websites, personalized recommendations and inventory tracking systems. Additionally, the system allows brands to identify fake products by examining subtle variations in packaging and design. Another advantage:

The proposed workflow combines GAN-based synthetic data, deep learning classification, and real-time application deployment to create an efficient and accurate cosmetic product identification system. This AI solution is a game-changer in the beauty industry, boasting advanced data pre-processing, high-quality synthetic image enhancement, and efficient model training.

V. TOOLS USED

Various tools and technologies are employed to classify cosmetic products with accuracy, provide effective training, or GANs, in a system that can be deployed real-time. Among the tools are deep learning frameworks, image pre-processing libraries, GAN architectures (general artificial neural networks), performance evaluation metrics, and model optimization techniques. Hence every tool we use helps to improve the efficiency, scalability and system accuracy.'

This study focuses on Tensor Flow and PyTorch, which are among the most commonly used deep learning frameworks. By offering neural network layers that are pre-built, characterized by automatic differentiation and GPU acceleration, these frameworks are well-suited for training both Generative Adversarial Network (GANs) and classification models With Tensor Flows optimization, edge devices can be inferred in real time, and PyTorch generative experimentation system offers flexible experimenting through its dynamic computational graph.

PIL (Python Imaging Library) and other tools are employed to pre-process and enhance images. To ensure input images are standardized before being fed into the model, OpenCV is used to assist with image correction, noise reduction and enhancement of contrast for smoother edges. Data enhancement techniques like rotation, flipping, and brightness modifications are made more robust by PIL when it is used to introduce variations in training data. This technique helps models become more stable.

Specialized architectures like PGGANs and C-GANS are utilized in the GAN-based synthetic image generation process. PyTorch and TensorFlow are utilized to implement these architectures, while libraries like Keras-GAN and NVIDIA Style GUN are used for fine-tuning synthetic image generation. The quality and diversity of images produced are assessed using GAN evaluation metrics like Fréchet Inception Distance (FID) and Injection Score (IS).

Scikit-learn is utilized to evaluate the classification model's success by calculating metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The metrics serve as a gauge of the model's ability to differentiate between cosmetic products that are visually similar. Matplotlib and Seaborn are among the tools used to visualize training progress, classification performance, and loss curves in order to help identify potential model problems. The second type (e.g. To make real-time deployment easier, there are several model optimization tools available, including TensorFlow Lite, ONNX (Open Neural Network Exchange), and NVIDIA TensorFlow, which aim to reduce the model size, improve inference speed, and support mobile/edge AI. The trained model can operate smoothly on smartphones, IOT devices, and cloud-based platforms with the help of these tools. This ensures accuracy. By incorporating these tools, the system is made capable of handling real-world scenarios in the identification of cosmetic products

VI. RESULT AND DISCUSSION

The system of proposed cosmetic products was tested using a dataset that included both real and synthetic images generated by GAN through extensive experiments. These findings indicate substantial enhancements in classification accuracy, dataset variability, and real-time performance compared to conventional methods. This part describes the quantitative and qualitative results, including effects of enhancement using GAN, classifier performance as well as system "robustness".

A significant finding is that the training dataset includes GAN-generated images, which aid in identifying cosmetics that appear similar to the model's appearance. The misclassification of products by traditional models was a challenge due to the limited variation in packaging, which made it challenging to train for these types of images. Even so, the incorporation of artificial images revealed improved feature extraction capabilities within the system, leading to a more accurate classification.

The classification accuracy of the hybrid dataset, which includes real and GAN-generated images, was 92.7% when tested with quantitative data, while it was only 84.5% when using real images alone. The 8.2% rise highlights the importance of GAN-based augmentation in managing data scarcity and unbalanced categories. Also, the measures of accuracy, recall, and F1-score were noticeably enhanced by the model, indicating that it effectively minimizes both false positives and false negatives.

To evaluate the quality of images produced with GAN, they used metrics such as Frechet Inception Distance (FID) and Injection Score (IS). The generated images had a FID score of 17.3, which suggests that they closely imitate real pictures (lower scores indicate lower similarity). With a score of 9.1, the synthetic images were found to have enough visual variety and some degree of originality. The outcomes demonstrate that GAN-generated images are advantageous for classifier training.

Traditional classification models were evaluated in comparison to the proposed GAN-assisted approach. When trained on real datasets, however it was difficult to generalize these models to unknown variations and lighting conditions. Even so, the proposed model, which was tested using a hybrid dataset, demonstrated greater flexibility with different lighting and background conditions as well as some slight packaging distortions.

Despite the fact that mobile cameras were used to capture images under various conditions, experiments conducted on real-world applications demonstrated that the system could still classify products with accuracy. This is particularly useful for e-commerce sites, retail apps and in real-time counterfeiting where users can identify products. By consistently performing well across different smartphone cameras, resolutions, and angles, the model was highly versatile. The unit also performed exceptionally well in various orientations.

Investigations into misclassification cases revealed that most errors occurred when there were almost identical products with only slight text differences on their packaging. Displacing font size or ingredient lists in the model was problematic due to its emphasis on extracting visual elements rather than recognizing text. In the future, multi-modal learning approaches may be utilized to combine OCR with image-based classification for improved accuracy.

Another significant topic of discussion is real-time system performance. After applying quantization and pruning techniques to optimize its design, the final model was able to infer data at 45 milliseconds per image, making it suitable for use on mobile and edge AI. This efficiency results in the user being able to identify products quickly and easily, which is crucial for adoption in practical applications.

The system's ability to identify counterfeit goods was also examined. Through the use of training that taught the classifier about subtle differences between genuine and fake cosmetic products, it was able to identify counterfeit products with an accuracy of 89.3%. Brands, retailers, and consumers can use this application to verify the legitimacy of beauty products before making a purchase.

A significant benefit of the GAN-based approach is its ability to address data imbalance issues. Cosmetic product datasets may exhibit biased models due to the insufficient training images for certain brands or categories. By augmenting underrepresented categories, the images generated by GAN contribute to a more balanced dataset, ensuring consistent performance across product types.

One of the limitations is the computational complexity of training GANs, which requires longer time frames on GPUs with high performance. However, once trained, the model can be deployed efficiently on light hardware. Future research may involve exploring faster training techniques for GANs, such as few-shot learning or efficient GAP architectures to minimize training costs.

The pilot testing of an e-commerce site yielded positive feedback from users, who expressed their satisfaction with the swift and precise identification of products. Users were generally satisfied with this experience. Despite this, some users expressed their desire for the integration of additional features, such as personalized recommendations and augmented reality (AR) try-on capabilities, to enhance the shopping experience.

Ultimately, the experimental results demonstrate that the proposed system has potential in identifying cosmetic products, detecting counterfeits, and is operational in real time. The use of a combination of GAN-based dataset augmentation, deep learning classification, and mobile optimization results in an extremely accurate, efficient, yet scalable, solution for the beauty industry. The system's performance will be enhanced by integrating OCR, expanding the dataset, and creating more efficient GAN architectures in future enhancements.

VIII. CONCLUSION

By utilizing Generative Adversarial Networks (GANs) the proposed system for identifying cosmetic products is designed to be more accurate and more efficient in product classification. The beauty and retail sectors find value in the system's ability to use deep learning techniques and generate synthetic data, which helps identify problems like packaging variability, lighting conditions, and counterfeit detection.

A significant accomplishment of this system is its ability to identify numerous cosmetic products with precision. This system eliminates the need for manual input and replaces traditional methods like barcode scanning and text-based searches, which often rely on inaccurate labels. This makes it a faster and easier way to go for consumers and retailers.

The system's ability to detect counterfeits is a significant feature. Additionally, through the examination of subtle variations in packaging, branding, and texture to identify potentially fraudulent products, the model is able to provide valuable insights into this. This feature is particularly beneficial for e-commerce sites, retail businesses, and brand manufacturers who want to safeguard their consumers from counterfeit products.

Synthetic images generated with GAN are used to enhance model performance. It is shown to improve classification accuracy and generalization, particularly with rare or less common products, by training with synthetic data. This method keeps the system robust and able to adjust to new product versions.

The proposed system's reliability can be confirmed by evaluating its performance through precision, recall, F1-score, and ROC-AUC metrics. This accuracy, misclassification rates, and inference time are extremely high compared to other systems of this kind. It is well-suited for applications such as supply chain management systems by retailers or online stores.

The system has significant advantages, including scalability and flexibility for deployment. The system can be easily integrated with existing retail and e-commerce platforms, as it relies on Flak and Django APIs. The model's ability to identify products on a large scale is guaranteed by its cloud-based deployment and GPU acceleration, which reduces latency.

However, the system is not without its fair share of problems and constraints. Changing designs on product packaging, which often involves changes from brands to new designs, is a significant challenge. The system incorporates a continuous learning approach to manage classification accuracy by periodically updating with new product images. This is done through periodic training sessions.

Future developments may involve the use of Natural Language Processing (NLP) for text searches and Block chain technology for counterfeit verification. The use of Block chain can enhance consumer confidence and transparency in cosmetics by providing dependable, unchanging records of verified products.

According to the results, AI-based cosmetic product identification systems could bring about a significant shift in retail and e-commerce. Such systems, when refined and embraced by industry, have the potential to enhance consumer satisfaction through user authentication of products, as well as improve supply chain efficiency.

The proposed system demonstrates a robust and adaptable method for identifying cosmetic products and detecting counterfeits. A combination of deep learning, synthetic data augmentation and real-time processing ensures accuracy while still being user friendly. As more features and improvements are made to existing systems, this system can play a significant role in guaranteeing authenticity, safety, and better shopping experiences for users in the global cosmetics market.

IX. REFERENCES

[1] Ian. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," Advances in Neural Information Processing Systems, vol. 27, 2014.

Available at: https://arxiv.org/abs/1406.2661

[2] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 770–778.

Available at: https://arxiv.org/abs/1512.03385

[3] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein GAN," arXiv preprint arXiv:1701.07875, 2017.

Available at: https://arxiv.org/abs/1701.07875

[4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

Available at: https://www.nature.com/articles/nature14539

[5] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive growing of GANs for improved quality, stability, and variation," in Proc. Int. Conf. Learn. Representations (ICLR), 2018.

Available at: https://arxiv.org/abs/1710.10196

[6] R. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," arXiv preprint arXiv:1511.06434, 2015.

Available at: https://arxiv.org/abs/1710.10196

[7] X. Huang, M. Liu, S. Belongie, and J. Kautz, "Multimodal unsupervised image-to-image translation," in Proc. Eur. Conf. Comput. Vis. (ECCV), 2018, pp. 172–189.

Available at: https://arxiv.org/abs/1804.04732

[8] H. Sajjad, A. Khan, and M. R. A. Raza, "Deep learning-based counterfeit detection in cosmetic products," in Proc. IEEE Int. Conf. Artif. Intell. Comput. Vis. (AICV), 2020, pp. 132–139.

Available at: https://ieeexplore.ieee.org/document/9096820

[9] Y. Zhang, J. Liu, and X. Zhang, "A convolutional neural network approach for brand logo recognition," Pattern Recognit., vol. 64, pp. 167–175, 2017.

Available at: https://www.sciencedirect.com/science/article/pii/S0031320316304121

[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in Proc. Adv. Neural Inf. Process. Syst. (NIPS), 2012, pp. 1097–1105.

Available at: https://proceedings.neurips.cc/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html

[11] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.

Available at: https://arxiv.org/abs/1409.1556

[12] G. Ghiani, F. Lamberti, and A. Sanna, "Deep learning-based methods for counterfeit detection in e-commerce," IEEE Access, vol. 8, pp. 193021–193033, 2020.

Available at: https://ieeexplore.ieee.org/document/9219226

[13] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in Proc. Adv. Neural Inf. Process. Syst. (NIPS), 2015, pp. 91–99.

Available at: https://arxiv.org/abs/1506.01497

[14] H. Lee, J. H. Hong, and J. H. Kim, "A GAN-based approach to data augmentation and counterfeit detection in online product authentication," IEEE Trans. Ind. Informat., vol. 16, no. 12, pp. 7702–7711, 2020.

Available at: https://ieeexplore.ieee.org/document/9115430

[15] P. Isola, J. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2017, pp. 1125–1134.

Available at: https://arxiv.org/abs/1611.07004

[16] H. Song, H. Kim, and H. Choi, "A deep learning-based counterfeit detection system using mobile applications," in Proc. IEEE Int. Conf. Consum. Electron. (ICCE), 2021, pp. 1–4.

Available at: https://ieeexplore.ieee.org/document/9374660

[17] M. Mirza and S. Osindero, "Conditional generative adversarial nets," arXiv preprint arXiv:1411.1784, 2014.

Available at: https://arxiv.org/abs/1411.1784

[18] S. Woo, J. Park, J. Lee, and I. S. Kweon, "CBAM: Convolutional block attention module," in Proc. Eur. Conf. Compute. Vis. (ECCV), 2018, pp. 3–19.

Available at: https://arxiv.org/abs/1807.06521

[19] EMG Controlled Bionic Robotic arm using artificial intelligence and Machine learning

Available at:

https://ieeexplore.ieee.org/document/9640623

[20] Facial Emotional Detection Using Artificial Neural Networks

Available at:

https://drive.google.com/file/d/1upKdWjQ767Ebaym7RH4rHUBj-RsEOAR8/view?usp=sharing

[21] Neural Network-based Alzheimer's Disease Diagnosis With Densenet-169 Architecture

Available at:

https://drive.google.com/file/d/1OymszZx-G52WhtvzTYJ0zj1DaQnLS0cY/view?usp=sharing

[22] Predicting Food Truck Success Using Linear Regression

Available at:

https://drive.google.com/file/d/14av3lwf29kCBs0hnp3oluTsVMdtUI7S4/view?usp=sharing

[23] Heart Disease Prediction Using Ensemble Learning Techniques

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[24] Movie Recommendation System Using Cosine Similarity Technique

Available at:

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[25] Flight Fare Prediction Using Ensemble Learning

Available at:
https://drive.google.com/file/d/1LpRuFHbLXW8d0n5q28B1vwbcqT-zaoFR/view?usp=sharing

[26] Clustered Regression Model for Predicting CO2 Emissions from Vehicles

Available at:
https://drive.google.com/file/d/1tRXQnTaqov0M7M0KYGMimkVErlN7ojvY/view?usp=sharing

[27] Optimized Conversion of Categorical and Numerical Features in Machine Learning Models

Available at:
https://ieeexplore.ieee.org/document/9640967

[28] Brain Tissue Segmentation via Deep Convolutional Neural Networks

Available at:
https://ieeexplore.ieee.org/document/9640635

[29] Forecasting Employee Attrition Through Ensemble Bagging Techniques

Available at:
https://drive.google.com/file/d/1j2h37BzOqxpt5UB98NlBDscU6tjZcGZz/view?usp=sharing

[30] Hand Gesture Recognition Using Artificial Neural Networks

Available at:
https://drive.google.com/file/d/1SIEAULz4yaoRmhv8uAz5l1z3CWV9YwRv/view?usp=sharing