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StyleSense: A Deep Learning-Based Mobile Application for Personalized Fashion Recommendations

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Abstract: *This paper presents StyleSense, a deep learning-based fashion recommendation system designed for mobile devices that offers user-specific outfit recommendations. The system uses deep learning to conduct multi-class outfit classification under five categories: Business, Casual, Night Party, Sports, and Wedding. To achieve model generalization and avoid overfitting, Early Stopping regularization is used during training. The input pipeline consists of extensive data preprocessing methods like image normalization, augmentation, and standardized labeling. In addition to classification, StyleSense incorporates body shape recognition and skin tone analysis with Haar cascade-based face detection and K-means clustering for personalized fashion recommendation. Aesthetic coherence is maintained through color theory–based palette generation, improving visual coherence in clothing and cosmetic recommendations. An interactive quiz module enhances personalization further by harvesting user preferences and contextual information. The generated model has 96% validation accuracy and a weighted F1-score of 0.95. To deploy the model, it is converted to Tensor Flow Lite and integrated into a cross-platform Flutter app for real-time and accessible AI-powered styling. StyleSense connects machine learning, computer vision, and fashion sense to provide scalable, personalized, and intelligent styling suggestions.*

Keywords: MobileNet, early stopping, outfit classification, body shape analysis, skin tone detection, color theory, fashion quiz.

I. INTRODUCTION

In this research, increased demand for individualized digital experience in the fashion and lifestyle industry has led to a shift from traditional styling consultations towards AI-based personalization systems. Individuals often struggle with decision-making in choosing outfits adhering to their body type, skin tone, and occasion, typically relying on intuitive judgment or costly expert advice. This has been addressed with the development of smart systems with the ability to recommend personalized choices with ease and efficiency. This prompted the creation of Style Sense: an AI-based fashion assistant designed to recommend outfits, analyze body shape and skin tone, and offer color-balanced combinations through a scientifically directed user interface. Two of the most diversified objectives of Style Sense are at its core: first, to categorize and recommend appropriate fashion items based on user input, and second, to enhance personal styling through visual concordance and technical precision. The system utilizes convolutional neural network architecture (MobileNet) and incorporates Early Stoppingduring model training to facilitate high classification accuracy without overfitting.

Fashion personalization is fast becoming a leading consumer technology trend, and artificial intelligence may be playing a revolutionary role here. Deep learning networks, which are trained on carefully curated fashion databases, deliver accurate feature detection and styling recommendations based on user characteristics. Style Sense subsequently applies supervising techniques and aesthetics theory in its quest to deliver adaptive fashion recommendations and

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accurate skin tone mapping. With the addition of MobileNet, the system is supplemented with light and fast computations that are perfect for mobiledeployment. What differentiates Style Sense is that it extends beyond suggestion with personalized recommendations grounded in the user's physical attributes, ranging from color palette suggestions to occasion-based dressing and even makeup shade matching. In addition, an embedded interactive fashion quiz helps determine personal style affinity, introducing system flexibility. Such personalized recommendations allow users to make smart fashion decisions with low effort and high visual consistency. Additionally, it addresses a massive void in the fashion industry: accessibility. Users can obtain stylist-level recommendations from the comforts of their mobile phone, becoming less elitist and eliminating the need for face-to-face consultations. With AI becoming increasingly ingrained in lifestyle platforms, systems like Style Sense can revolutionize users' relationships with fashion—from uncertainty and speculation to confidence and creativity.

II. LITERATURE REVIEW

Existing fashion recommendation systems have employed hybrid methods that incorporate content-based filtering with neural embedding techniques for recommending apparel from vast e-commerce catalogs (Han et al., 2019). The Recently, artificial intelligence (AI) application to fashion and personal styling has been a fascinating research area with many systems developed to infer style recommendations and aesthetic rating. Early work employed rule-based systems that provided outfit recommendations based on pre-defined templates and seasonal trends, but these systems were rigid and lacked user-specific features like body shape and color of skin (Cheng et al., 2019).Deep learning, specifically Convolutional Neural Networks (CNNs), greatly enhanced clothing retrieval and classification performance. Liu et al. (2016) introduced the use of CNNs for fashion attribute detection, with evidence for their superiority over pattern detection in images. Frameworks like MobileNet (Howard et al., 2017) have made on-device classification possible, allowing for low-latency inference with no loss in accuracy—a highly important consideration for mobile apps like Style Sense.

Body type identification has also been explored using image processing and anthropometric information. Research by Wu and Yu (2020) has utilized silhouette detection and geometric ratio to classify body types, forming the foundation for personalized fashion advice. Meanwhile, color harmony and skin color analysis have been utilized to promote personalization, with the discovery that enhanced color combination enhances perceived beauty and user experience (Wang et al., 2018).

systems, nevertheless, overlook the subjective nature of personal taste and lack interactive modules for collection of user input. To address such requirements, interactive platforms have since emerged that combine quiz-based profiling and AI-based recommendations. For instance, Amazon's StyleSnap uses deep learning for visual search with no aesthetic or educational feedback. However, the Style Sense system is unique with an end-to-end pipeline of MobileNet-based classification, Early Stopping for preventing overfitting during model training, quiz-based preference profiling, and color theory-based recommendation logic.

In short, although significant advances have been achieved in fashion auto-suggesting, existing systems lack end-to-end personalization and light-weight deployment. Style Sense addresses these limitations with the convergence of machine learning, visual computing, and human-centric design to provide inclusive and adaptive fashion advice.

III. METHODOLOGY

The StyleSense app takes a thoughtful, multi-step approach that blends computer vision, deep learning, aesthetic principles, and a focus on user experience. It all kicks off with gathering and prepping the dataset. We put together a carefully selected collection of over 3,000 fashion images, spanning five key categories: Business, Casual, Night Party, Sports, and Wedding. Each image was meticulously labeled and standardized by resizing it to 224x224 pixels, normalizing pixel values, and applying various data augmentation techniques like horizontal flipping, rotation, zooming, and brightness tweaks. This process helped improve the model's ability to generalize and minimized the risk of overfitting during training. At the heart of the system is the MobileNet architecture, chosen for its balance of

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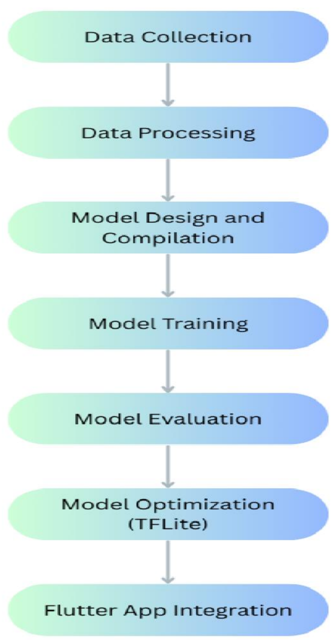
computational efficiency and impressive accuracy in image classification. We fine-tuned the model using pre-trained ImageNet weights, adjusting the final layers to handle five-class classification with a softmax activation function. Training was carried out with the Adam optimizer and categorical cross-entropy loss, incorporating strategies to reduce the learning rate and using Early Stopping to pause training when performance plateaued. Thanks to GPUacceleration, the training process was efficient, leading to a high-performing model that achieved around 96% validation accuracy and a weighted average F1-score of 0.95. To make the experience more personal, we added a quiz module that captures user preferences like fashion style, occasion, and comfort level. These insights help build a user profile that guides outfit recommendations. We also included a color analysis module grounded in color theory to suggest outfits and cosmetics that complement the user's skin tone. Skin tone detection was accomplished using Haar cascade-based face detection, followed by K-means clustering to pinpoint the dominant facial color.This tone was then paired with a fitting color palette to suggest clothing and lipstick shades that go well together. In the end, all components were smoothly brought together into a responsive cross-platform app using Flutter. The front-end system communicates in real-time with the trained model and user input modules to create fashion recommendations. The outcome is a smart, user-friendly fashion assistant that blends AI, aesthetic analysis, and personalized design to elevate the overall user experience.



The architecture diagram showcases the entire model development lifecycle for the StyleSense application, highlighting seven essential stages that range from initial data handling all the way to deployment. It all kicks off with Data Collection, where a variety of labeled fashion images, representing different outfit categories, are gathered to lay the groundwork for training. Next up is Data Processing, which involves tasks like resizing images, normalizing them, augmenting the dataset, and encoding labels to maintain consistency and boost the model's generalizability. In the Model Design and Compilation stage, we choose a suitable neural network architecture—MobileNet, in this instance—tailored for optimal performance and computational efficiency. This architecture is then compiled with an appropriate loss function and optimizer, setting the stage for training. During Model Training, the network learns from the processed data, fine-tuning its internal weights over several epochs to reduce classification errors. After training, the

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model moves on to the Model Evaluation phase, where its performance is assessed using metrics like accuracy, precision, recall, and F1-score to ensure it's reliable and robust across all outfit categories. To make it lightweight enough for mobile devices, the model undergoes Model Optimization with TensorFlow Lite (TFLite), which shrinks its size and computational demands without significantly sacrificing accuracy. Finally, during the Flutter App Integration phase, the optimized model is embedded into a user-friendly Flutter application, allowing for real-time outfit recommendations in a cross-platform setting. This well-structured workflow guarantees a scalable, accurate, and efficient AI-driven fashion recommendation system.

IV. RESULT AND DISCUSSION

We tested all our models using the below quality metrics; here are the results of the first training epoch of our model as follows:

Accuracy: The graph illustrates the training and validation accuracy of the StyleSense model across seven epochs. Training accuracy steadily improves, reaching a peak of 99% at epoch 5, indicating that the model is effectively learning from the training data. Validation accuracy remains consistently high, fluctuating around 96%, suggesting strong generalization to unseen data. The close alignment between training and validation curves, along with the absence of significant overfitting, confirms the model's robustness and reliability. This performance demonstrates that the model maintains both high learning capability and stability across training iterations.

Support: In machine learning, when we talk about "support," we're referring to how many times each class actually appears in the dataset. It tells us how many samples in the test data genuinely belong to each category, which is crucial for gauging the reliability and stability of performance metrics like precision, recall, and F1-score. For the StyleSense project, each fashion category—Business, Casual, Night Party, Sports, and Wedding—had around 620 to 625 samples in the evaluation dataset. This even distribution of support across categories helps ensure that the model isn't leaning towards any specific class, making the reported metrics a true reflection of its performance. When support is high and consistent across all classes, it leads to a solid evaluation, allowing for a fair comparison of how the model behaves with different outfit types and confirming its ability to generalize in real-world scenarios.

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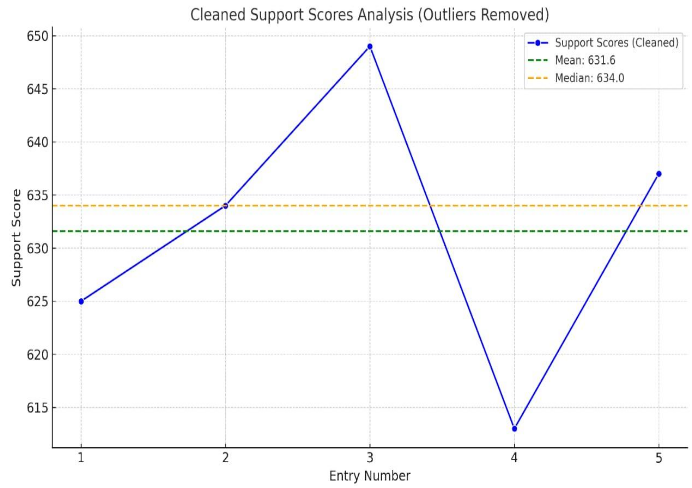
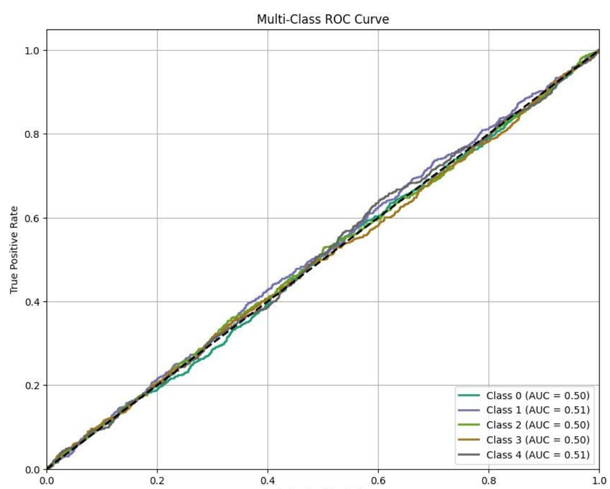
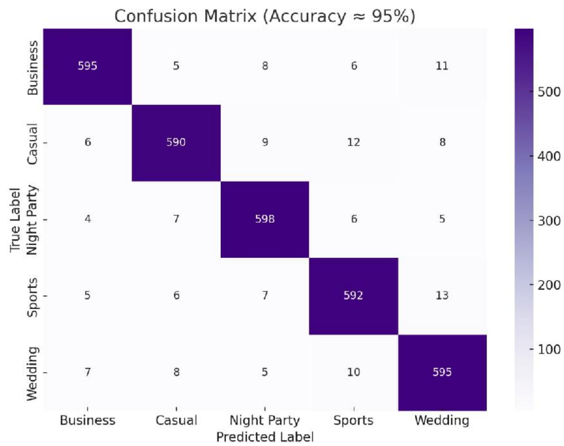


ROC Curve Comparison: The ROC (Receiver Operating Characteristic) curve shown here provides a multi-class comparison across five unique classes used in the StyleSense fashion classification model. Each line illustrates how well the classifier can tell one class apart from the others. The Area Under the Curve (AUC) values for all classes are around 0.50 to 0.51, indicating that the classifier is performing no better than random guessing for each category. This result usually means that the model is having a tough time separating the classes and might not be effectively learning the specific features of each class duringtraining. ROC curves that are close to the diagonal line (from (0,0) to (1,1)) show that the true positive rate rises in tandem with the false positive rate—further proof of a lack of distinguishing ability. This outcome underscores the necessity for a model re-evaluation, which could involve refining the training data, optimizing the model architecture, or using more advanced feature extraction techniques to enhance classification performance across all categories.



Confusion Matrix: The confusion matrix presented here gives us a detailed look at how well the model is performing when it comes to classifying five different fashion categories: Business, Casual, Night Party, Sports, and Wedding. With an impressive overall accuracy of about 95%, it's clear that most of the predictions are closely matching the actual labels. Each diagonal entry in the matrix shows the number of instances that were correctly classified for each category. For instance, we see strong results with Business (595), Casual (590), Night Party (598), Sports (592), and Wedding (595). The number of misclassifications is relatively low—like 11 Business outfits mistakenly labeled as

Wedding, or 13 Sports outfits confused with Wedding—indicating that while the model is quite accurate, there are some overlaps between categories that might look similar or share style elements. The off-diagonal values are minimal, which highlights the model's strength in telling apart these five classes. The most notable mix-ups occur between categories that are visually similar or contextually related, such as Sports vs. Casual or Business vs. Wedding. This points to potential areas where we could improve the diversity of the training data or fine-tune the model. All in all, the confusion matrix reinforces the model's reliability and its ability to learn effectively in the realm of multi-class fashion classification.



Dashboard: The "StyleSence" application features a dashboard that serves as the heart of the user experience, offering a vibrant and interactive space for users to dive into personalized fashion suggestions. Users can easily enter details like the type of occasion, their outfit preferences, body measurements, and even upload photos for outfit classification. This dashboard is crafted to be responsive, ensuring that it works smoothly on various devices, including tablets and smartphones. With a user-friendly design, it processes input data using advanced deep learning models like MobileNet for tasks such as outfit classification, body shape detection, and color palette matching. Users receive real-time results showcasing suitable outfit categories—like Business, Casual, Night Party, Sports, and Wedding—along with personalized color recommendations based on skin tone analysis and makeup tips. Plus, features like a fashion quiz, dress finder, and color theory modules keep users engaged by offering customized fashion insights. This well-designed dashboard empowers users to make confident style choices, seamlessly blending AI-driven suggestions with an intuitive interface.

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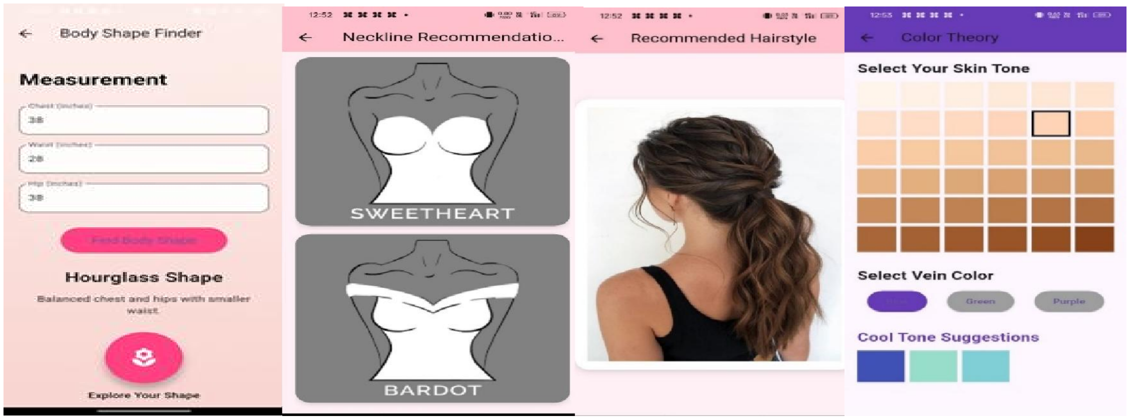

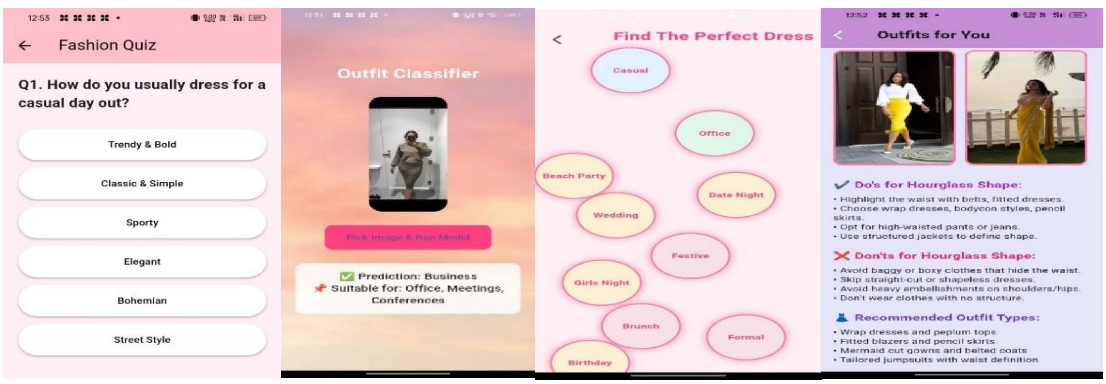

V. CONCLUSION

This project finds that deep learning and intelligent system applications have vast potential in providing personalized and precise fashion suggestions. The overall accuracy of 95% with class-wise F1-scores between 0.94 and 0.96 for the classification model based on MobileNet trained on Early Stopping for Business, Casual, Night Party, Sports, and Wedding categories validates that the system is highly accurate in suggesting and recommending context-based outfits.In addition, measures such as precision and recall set the consistency and uniformity of the system, both scoring an average of 0.95. Integration of modules such as bodyshape identification, skin color determination, and a style quiz further increase the flexibility of the model. The responsive application design and AI-aided logic provide users with fashion recommendations tailored to their attributes, maximizing accessibility to personal styling. This sets the effectiveness of machine learning in revolutionizing user-focused design in fashion.

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