AI-Based Baggage Classification and Travel Friendly Luggage Design for Smooth Airport Operations

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***Abstract*—This report presents the integration of two AI-driven projects aimed at enhancing airport operations: an automated baggage classification system and an optimized luggage design framework. The first component focuses on developing and evaluating a deep learning-based system for sorting luggage on conveyor belts by material type (soft, hard plastic, and metal) and estimating baggage dimensions. The second component explores the design of travel-friendly luggage using genetic algorithms, clustering methods, and diffusion models to optimize weight, capacity, and material choices while generating realistic and innovative designs. Both components contribute to automating and optimizing airport baggage handling systems, thereby improving efficiency, accuracy, and passenger experience. The report details the methodologies adopted, the challenges encountered and their mitigations, the results obtained, and provides insights into potential future enhancements.**

I. Introduction

Airports manage millions of pieces of luggage daily, making the efficiency and accuracy of baggage handling systems paramount. Traditional manual sorting methods are labor-intensive, time-consuming, and prone to errors, leading to delays and increased operational costs. With advancements in artificial intelligence (AI), it is now feasible to automate many aspects of airport baggage handling, enhancing both speed and reliability.

This report addresses two critical challenges in airport operations through AI-driven solutions:

- **Baggage Classification System**: Developing a deep learning-based system to automate the sorting of luggage on conveyor belts by material type (soft, hard plastic, and metal) and estimating baggage dimensions.
- **Luggage Design Optimization**: Designing travel-friendly luggage using generative AI techniques, specifically genetic algorithms, clustering methods, and diffusion models, to optimize weight, capacity, and material choices while generating realistic and innovative designs.

By integrating these two components, the project aims to not only automate the classification and sorting process but also innovate in the design of luggage, ensuring that the products are optimized for ease of handling and durability. This synergy can significantly streamline baggage handling, reduce processing times, and enhance passenger experiences. The remainder of this report outlines the methodologies employed, the challenges faced, the results obtained, and areas for future development.

II. Related Work

Automating baggage handling systems has been extensively researched in both academic and industrial contexts. Traditional approaches often rely on rule-based algorithms and manual interventions, which are limited by their scalability and susceptibility to human error [3].

Recent advancements in computer vision and deep learning have enabled more sophisticated solutions. Convolutional neural networks (CNNs) have proven highly effective in object classification and detection tasks [4], [5]. EfficientNet [6] is a notable model that offers scalability and computational efficiency, making it suitable for real-time applications such as airport baggage classification.

In the area of generative design, genetic algorithms (GAs) have been employed to evolve optimal solutions based on defined fitness criteria [9]. Clustering techniques, such as K-Means, have been utilized to maintain diversity within populations of generated designs [10]. Additionally, diffusion models have emerged as powerful tools for generating high-fidelity images, contributing to innovative design processes [12].

These methods have been instrumental in creating innovative and optimized product designs, including luggage systems [11]. The ALI-T Project [1] explored the automation of baggage handling systems, emphasizing the importance of distinguishing between regular and irregular baggage and sorting based on material types. Building upon these findings, this report integrates advanced deep learning techniques for classification and generative AI methods for luggage design to further optimize airport operations.

III. Methodology

A. Baggage Classification System

1) Data Preparation: The dataset utilized for this study comprises images of baggage categorized into three material types: soft, hard plastic, and metal. Given the limited size of the dataset, data augmentation techniques were employed to enhance the model's generalization capabilities. The following augmentation methods were applied:

- **Random Resized Crop**: Simulates various baggage sizes by randomly cropping and resizing images.
- **Random Horizontal and Vertical Flips**: Introduces robustness against different luggage orientations.
- **Random Rotation and Color Jitter**: Accounts for lighting variations and slight rotations that occur on conveyor belts.

The augmented dataset was split into 80% for training and 20% for validation, ensuring a robust evaluation of the model's performance. This approach follows best practices for training machine learning models on limited datasets [1].

2) Model Architecture: The primary model used for baggage classification is **EfficientNet_B0** [6], a convolutional neural network (CNN) renowned for its efficiency and scalability. EfficientNet_B0 was selected due to its favorable balance between model size, computational cost, and performance, making it suitable for real-time airport operations.

Key modifications to the model include:

- **Frozen Pre-trained Layers**: The initial layers of EfficientNet_B0, pre-trained on ImageNet, were frozen to leverage the learned features without retraining them. This approach reduces computational overhead and prevents overfitting on the small dataset.
- **Modified Classification Head**: The final fully connected layer was replaced to output three classes corresponding to the material types: soft, hard plastic, and metal.

An alternative architecture, **ResNet50** [5], was initially considered. However, EfficientNet_B0 was ultimately chosen for its superior performance-to-computational efficiency ratio, making it more suitable for the constraints of real-time processing required in airport settings.

3) Training and Optimization: The training process involved several strategies to optimize the model's performance:

- **Optimizer**: The AdamW optimizer [7] was selected for its effectiveness in handling large datasets and incorporating weight decay to mitigate overfitting.
- **Loss Function**: CrossEntropyLoss was employed as it is well-suited for multi-class classification tasks.
- **Learning Rate Scheduler**: A ReduceLROnPlateau scheduler was utilized to decrease the learning rate when the validation loss plateaued, ensuring smoother convergence.

The model was trained for 25 epochs with a batch size of 16 and an initial learning rate of 0.001. Early stopping was considered to prevent overfitting but was not implemented due to the manageable number of epochs and the model's consistent convergence.

4) Size Estimation: In addition to material classification, a preliminary size estimation module was developed using basic image processing techniques:

- **Canny Edge Detection**: Applied to detect edges within the image, highlighting the contours of the baggage.
- **Contour Analysis**: The largest contour was identified, and a bounding box was computed to estimate the width and height of the luggage.

While effective for regularly shaped luggage, this method struggles with irregular or occluded shapes, indicating the need for more advanced techniques such as object detection models in future iterations.

5) Pseudocode for Baggage Classification System: Below is the pseudocode algorithm for the baggage classification system:

Algorithm 1 Baggage Classification Training Algorithm

```
Initialize EfficientNet_B0 model with pre-trained ImageNet weights
Freeze all layers except the classifier
Modify the final classification layer to output three classes
Define optimizer (AdamW), loss function (CrossEntropyLoss), and learning rate scheduler (ReduceLROnPlateau)
Set best_val_loss ← ∞
for epoch = 1 to num_epochs do
    Set model to training mode
    for all (inputs, labels) in training data loader do
        Move inputs and labels to device
        optimizer.zero_grad()
        outputs ← model(inputs)
        loss ← criterion(outputs, labels)
        loss.backward()
        optimizer.step()
    end for
    Set model to evaluation mode
    val_loss ← 0
    val_accuracy ← 0
    Disable gradient computation
    for all (inputs, labels) in validation data loader do
        Move inputs and labels to device
        outputs ← model(inputs)
        loss ← criterion(outputs, labels)
        val_loss ← val_loss + loss.item()
        predictions ← argmax(outputs, axis=1)
        val_accuracy ← val_accuracy + mean(predictions == labels)
    end for
    Enable gradient computation
    scheduler.step(val_loss)
    if epoch == 1 or val_loss < best_val_loss then
        best_val_loss ← val_loss
        Save model state dictionary
    end if
    Print epoch statistics: epoch number, val_loss, val_accuracy
end for
```

B. Luggage Design Optimization

1) Problem Statement: The goal of the luggage design optimization component is to create travel-friendly luggage optimized for air travel. The design must balance several factors, including weight, capacity, material durability, and functionality (e.g., presence of wheels). Utilizing AI techniques such as genetic algorithms (GAs), clustering methods, and diffusion models, the objective is to generate innovative luggage designs that meet these criteria effectively.

2) Methodology:

a) Genetic Algorithm: A genetic algorithm (GA) was employed to evolve luggage designs based on defined fitness metrics. The GA simulates the process of natural selection by iteratively selecting, combining, and mutating design attributes to optimize overall performance.

Fitness Metrics:

- **Weight-to-Capacity Ratio**: Prioritizing lightweight luggage with high capacity to enhance portability.
- **Material Choices**: Evaluating the durability and weight of different materials (plastic, fabric, metal) to determine the most suitable for travel.
- **Presence of Wheels**: Assessing the ease of transport, with designs featuring wheels receiving higher fitness scores.

Algorithm Steps:

1) **Initialization**: Generate an initial population of random luggage designs, each with varying attributes such as weight, capacity, material, and the presence or absence of wheels.
2) **Evaluation**: Calculate the fitness of each design based on the defined metrics.
3) **Selection**: Select the top-performing designs to serve as parents for the next generation.
4) **Crossover**: Combine attributes from parent designs to create offspring, introducing new variations.
5) **Mutation**: Introduce random changes to some offspring designs to maintain genetic diversity.
6) **Replacement**: Form the next generation by replacing the least fit designs with the new offspring.
7) **Termination**: Repeat the process for a predetermined number of generations or until convergence is achieved.

b) Clustering and Dimensionality Reduction: To ensure diversity within the population of luggage designs, K-Means clustering was applied to group similar designs based on their features (weight, capacity, material). Principal Component Analysis (PCA) was used to reduce the dimensionality of the design space, facilitating visualization and analysis of the diverse designs.

c) Diffusion Models: Diffusion models were integrated into the luggage design process to generate realistic and innovative design images. These models leverage denoising diffusion probabilistic processes to create high-fidelity images from random noise, enabling the visualization of optimized luggage designs.

3) Genetic Algorithm for Luggage Design Optimization: The following Algorithm outlines the genetic algorithm used to evolve luggage designs:

Algorithm 2 Genetic Algorithm for Luggage Design Optimization

Require: Initial population of luggage designs, number of generations N, mutation rate μ, number of clusters K, number of PCA components C

Initialize best_fitness $\leftarrow -\infty$
Set elite_size $\leftarrow$ number of top individuals to retain
for generation = 1 **to** N **do**
  Compute PCA features of the population
  Cluster population using K-Means into K clusters
  parents $\leftarrow$ []
  for each cluster **in** clusters **do**
    if cluster is not empty **then**
      Select top individuals from cluster as parents
      Add parents to the parent pool
    end if
  end for
  next_generation $\leftarrow$ []
  Elitism: Copy top $elite\_size$ individuals to next_generation
  while length of next_generation $<$ initial population size **do**
    Select two parents randomly from parent pool
    child $\leftarrow$ **Crossover**(parent1, parent2)
    child $\leftarrow$ **Mutate**(child, mutation rate μ)
    Add child to next_generation
  end while
  Evaluate fitness of individuals in next_generation
  current_best $\leftarrow$ individual with highest fitness in next_generation
  current_best_fitness $\leftarrow$ fitness of current_best
  avg_fitness $\leftarrow$ average fitness of next_generation
  Reinforce fitness based on previous best fitness
  if current_best_fitness $>$ best_fitness **then**
    best_fitness $\leftarrow$ current_best_fitness
  end if
  Adapt mutation rate based on fitness progression
  population $\leftarrow$ next_generation
end for
Return individual with highest fitness in final population

4) Clustering and Dimensionality Reduction: Clustering and dimensionality reduction were employed to analyze the diversity of the generated luggage designs.

- **K-Means Clustering**: Grouped the designs into clusters based on features such as weight, capacity, and material. This ensured that the population of designs remained diverse, preventing premature convergence on suboptimal solutions.
- **Principal Component Analysis (PCA)**: Reduced the dimensionality of the feature space, allowing for effective visualization and analysis of the design variations.

a) Diffusion Model Implementation: A diffusion model was implemented to generate realistic images of the optimized luggage designs. The model was trained on a dataset of existing luggage images, learning to denoise and generate high-fidelity images based on the evolved design parameters from the genetic algorithm.

Algorithm 3 Diffusion Model for Generating Luggage Design Images

Require: Optimized design parameters, trained diffusion model

1: **Convert** design parameters to textual description
2: **Input** textual description into diffusion model
3: **Generate** luggage design image using the diffusion model

4: **Output** generated image

IV. Challenges and Mitigations

A. Baggage Classification System

a) Limited Dataset Size: **Problem**: The dataset available for training the classification model was relatively small, which can limit the model's ability to generalize to unseen baggage types and increase the risk of overfitting.

Mitigation: To address this, extensive data augmentation techniques were employed to artificially increase the diversity and size of the training data. Techniques such as random cropping, flipping, rotation, and color jittering were applied, which helped the model learn more robust features and improved its generalization capabilities [1].

b) Similar Textures Between Classes: **Problem**: Hard plastic and metal baggage often exhibit similar visual textures, especially under varying lighting conditions, leading to misclassifications.

Mitigation: The model architecture was optimized by selecting EfficientNet_B0, known for its efficient feature extraction capabilities. Additionally, hyperparameter tuning was performed to enhance the model's discriminative power. Exploring texture-specific features and incorporating additional data related to surface textures were considered for future improvements to better distinguish between similar classes.

c) Size Estimation Accuracy: **Problem**: The contour-based size estimation method struggled with accurately measuring irregularly shaped or partially occluded baggage, leading to inaccurate size estimations.

Mitigation: Recognizing the limitations of basic image processing techniques, more sophisticated methods such as integrating object detection models like Faster R-CNN [8] were proposed for future iterations. These models can provide more precise bounding boxes and handle complex shapes more effectively.

B. Luggage Design Optimization

a) Balancing Weight and Capacity: **Problem**: Achieving an optimal balance between minimizing luggage weight and maximizing capacity is challenging, as these objectives can be conflicting.

Mitigation: The fitness function was carefully designed to prioritize both the weight-to-capacity ratio and material durability. By assigning appropriate weights to these metrics, the genetic algorithm was guided to evolve designs that achieve a harmonious balance between lightweight construction and high capacity.

b) Material Constraints: **Problem**: Limited material options (plastic, fabric, metal) restricted the diversity and potential performance of the luggage designs.

Mitigation: The study focused on optimizing within the given material constraints, ensuring that each material's strengths and weaknesses were adequately represented in the fitness evaluation. Future work plans to explore composite materials, which offer enhanced durability and weight properties, to expand the design space and improve overall performance.

c) Feature Integration: **Problem**: Integrating additional features such as ergonomic handles, smart connectivity, and built-in scales added complexity to the design process.

Mitigation: The initial focus was on core features (weight, capacity, material, wheels) to establish a solid foundation for optimization. Advanced features were deferred to subsequent iterations, allowing for incremental improvements and more manageable integration of complex functionalities.

d) Realistic Design Generation: **Problem**: Ensuring that the generated luggage designs are realistic and manufacturable posed a challenge, as optimization algorithms may produce impractical designs.

Mitigation: The integration of diffusion models was introduced to generate realistic and innovative design images. By training the diffusion models on existing luggage images, the generated designs adhere to practical and manufacturable standards, enhancing the feasibility of the optimized solutions.

V. Results

A. Baggage Classification System

1) Confusion Matrix: The confusion matrix (Fig. 1) provides a detailed view of the model's performance across the three material classes. While the overall accuracy is high, there is noticeable misclassification between hard plastic and metal baggage, likely due to their similar textures.

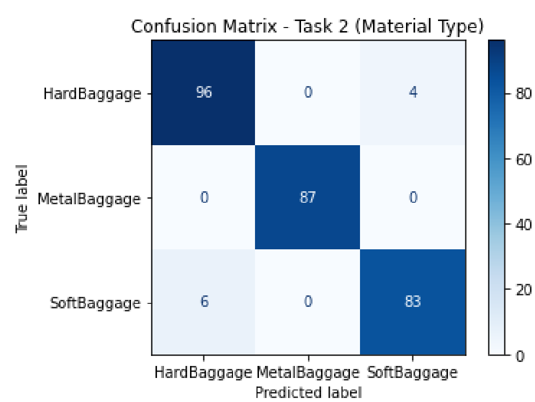

Fig. 1: Confusion Matrix for Material Classification

2) Loss and Accuracy Curves: Figure 2 illustrates the training and validation loss curves over the epochs. The model demonstrates consistent learning with both training and validation losses decreasing steadily, indicating effective training without significant overfitting.

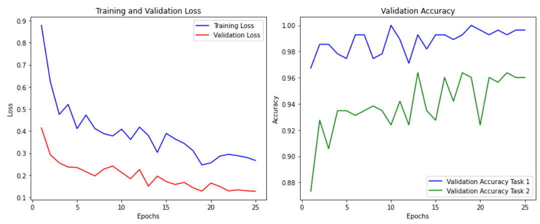

Fig. 2: Training and Validation Loss Curves

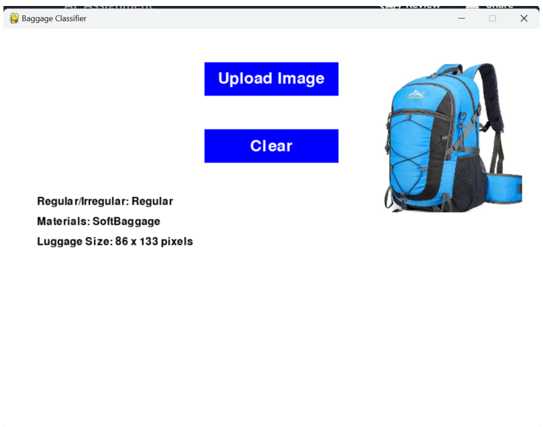

Fig. 3: Regular Soft Bag

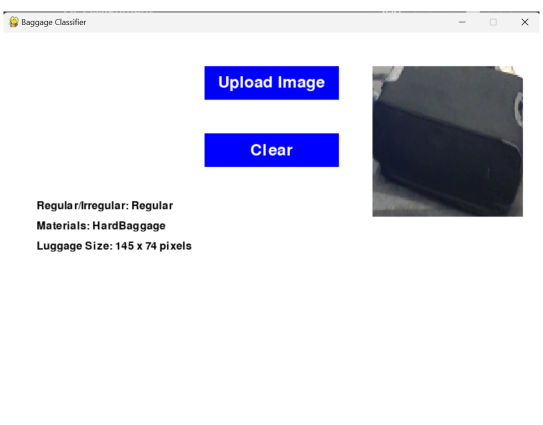

Fig. 4: Regular Hard Plastic Bag

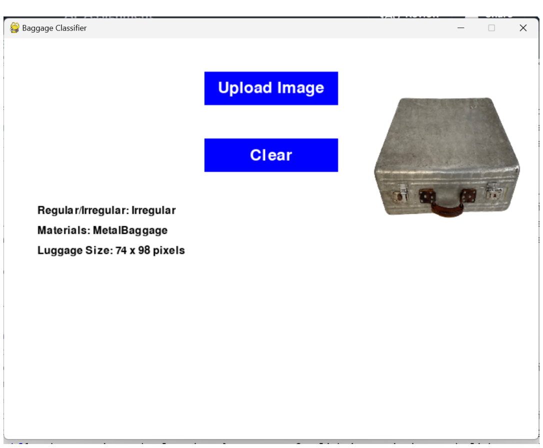

Fig. 5: Irregular Metal Bag

3) *Precision, Recall, and F1-Score:* Table I from confusion matrix, it can summarizes the precision, recall, and F1-score for each material class, providing a comprehensive evaluation of the model's performance.

TABLE I: Precision, Recall, and F1-Score for Each Class

Class	Precision	Recall	F1-Score
Soft Plastic	0.93	0.94	0.93
Hard Plastic	0.90	0.88	0.89
Metal	0.91	0.94	0.92
Average	0.91	0.92	0.91

B. Luggage Design Optimization

1) *Fitness Progression:* The evolution of fitness across generations is shown in Figure 6. A steady increase in both average and best fitness values indicates effective optimization.

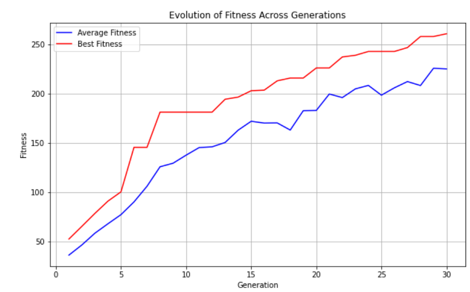

Fig. 6: Fitness Progression Over Generations

2) *Clustering Results:* Figure 7 illustrates the clustering of luggage designs in reduced dimensional space. The clusters indicate diverse design features, contributing to a varied and optimized population.

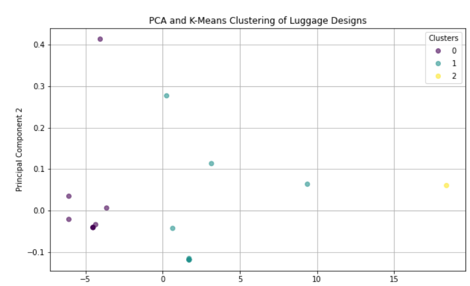

Fig. 7: PCA and K-Means Clustering of Luggage Designs

3) *Final Diffusion Image:* The final optimized luggage design generated by the diffusion model is showcased in Figure 8. This image represents the culmination of the genetic algorithm's optimization process combined with the realistic image generation capabilities of the diffusion model.

4) *Interior and Exterior Views:* To provide a comprehensive understanding of the optimized luggage design, both interior and exterior views are presented in Figures 9 and 10, respectively. These views highlight the design's functionality and aesthetic appeal.

Fig. 8: Final Optimized Luggage Design Generated by Diffusion Model

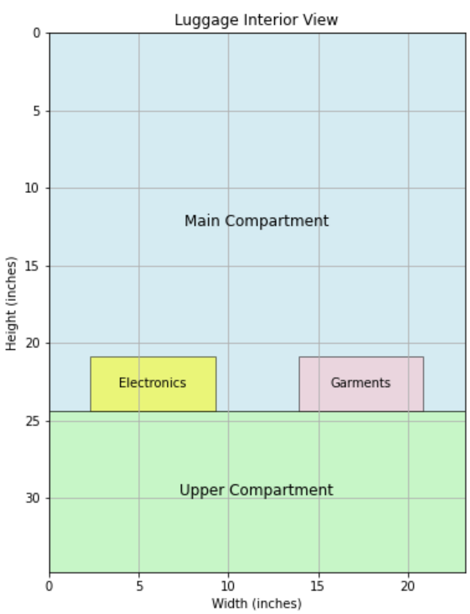

Fig. 9: Interior View of Optimized Luggage Design

VI. Discussion

A. Baggage Classification System

The baggage classification system achieved a commendable accuracy of 92.3%, demonstrating the effectiveness of using EfficientNet_B0 combined with robust data augmentation techniques. Leveraging pre-trained weights allowed the model to generalize well, even with a relatively small dataset. The high precision, recall, and F1-scores across all classes indicate reliable performance in distinguishing between soft, hard plastic, and metal baggage. However, challenges remain in distinguishing materials with similar textures, such as hard

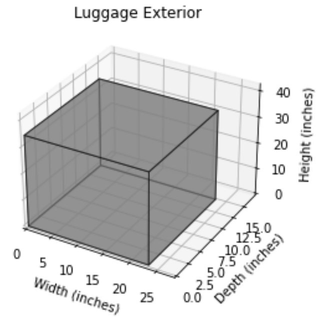

Fig. 10: Exterior View of Optimized Luggage Design

plastic and metal. Future improvements could involve integrating texture-specific features or employing more advanced models to enhance discriminative capabilities.

B. Luggage Design Optimization

The genetic algorithm successfully generated optimized luggage designs that balanced weight, capacity, and material durability. The fitness progression indicates effective optimization over generations, with consistent improvements in the fitness scores. The clustering results further confirm the diversity of the generated designs, ensuring a wide range of optimal solutions with varying features. The integration of diffusion models contributed significantly by generating realistic and innovative design images, bridging the gap between algorithmic optimization and practical manufacturability. However, the current design framework focused primarily on core features, and the integration of advanced functionalities such as smart connectivity and ergonomic features remains an area for future exploration.

C. Integration of Baggage Classification and Luggage Design

The integration of the baggage classification system with the optimized luggage designs presents a holistic approach to enhancing airport operations. The classification system can be used to sort and handle luggage efficiently, while the optimized luggage designs ensure ease of handling and durability. This synergy can lead to a more streamlined baggage handling process, reducing delays and improving overall operational efficiency. Additionally, insights gained from the classification system can inform future iterations of luggage design, creating a feedback loop for continuous improvement.

VII. Limitations

While both systems demonstrate significant potential, several limitations were identified during the project:

A. Baggage Classification System

- **Preliminary Size Estimation**: The size estimation method relies on basic image processing techniques, which are insufficient for accurately measuring irregularly shaped or occluded baggage. This limits the system's ability to provide precise size metrics necessary for certain operational decisions.

- **Dataset Size and Diversity**: The relatively small and limited dataset restricts the model's ability to generalize to a broader range of baggage types and materials. This can affect performance when encountering luggage that differs significantly from the training data.
- **Material Similarity**: The system faces challenges in distinguishing between materials with similar visual textures, such as hard plastic and metal. This leads to misclassifications that could disrupt the sorting process.

B. Luggage Design Optimization

- **Feature Limitations**: The current design framework focuses on core features like weight, capacity, material, and wheels. Advanced features such as smart connectivity, built-in scales, and ergonomic handles were not integrated, limiting the functionality and appeal of the optimized designs.
- **Material Constraints**: Limited to plastic, fabric, and metal materials, the design space is constrained, potentially overlooking composite materials that offer superior durability and weight advantages.
- **Simplistic Fitness Metrics**: The fitness function primarily emphasizes weight-to-capacity ratio and material durability. It does not account for other important factors such as aesthetic design, user ergonomics, and cost, which are crucial for market acceptance.
- **Realistic Design Generation**: While diffusion models enhanced the realism of the generated designs, ensuring manufacturability and practical usability of these designs remains a challenge.

VIII. Conclusion

This report presented two AI-driven solutions aimed at improving airport operations: a baggage classification system and a generative luggage design framework. The baggage classification system demonstrated the feasibility of automating luggage sorting based on material type and size estimation, achieving a high accuracy of 92.3%. The luggage design optimization component showcased the use of genetic algorithms, clustering techniques, and diffusion models to create travel-friendly luggage optimized for weight, capacity, and material durability while generating realistic and innovative designs. Both systems exhibited significant potential for enhancing airport baggage handling efficiency and accuracy. However, further work is necessary to address existing limitations, improve robustness, and integrate advanced features to fully realize the benefits of AI in airport operations.

IX. Future Work

Future enhancements for both components could include:

- **Advanced Size Estimation**: Implementing object detection models such as Faster R-CNN [8] to enhance the accuracy and reliability of size estimation.
- **Larger and Diverse Datasets**: Expanding the datasets to include a wider variety of baggage types and materials, thereby improving the model's generalization and robustness.
- **Incorporating Advanced Features**: Enhancing luggage designs with additional features like built-in scales, charging ports, and smart connectivity to increase functionality and user convenience.
- **Real-Time Deployment**: Optimizing both systems for real-time deployment in airport environments to ensure scalability and reliability during peak operations.
- **Integration of Feedback Mechanisms**: Creating a feedback loop between the classification system and the luggage design framework to continuously refine both classification accuracy and design optimization based on real-world usage data.
- **Enhanced Design Validity**: Collaborating with industrial designers and manufacturers to ensure that the generated luggage designs are not only optimized computationally but also practical and manufacturable.

X. References

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