BodyMax AI: Using Image-to-Image Machine Learning to Predict Potential Body Transformation

Daniyal Mohammed
Department of Computer Science
University of Waterloo
Waterloo, ON, Canada
d25moham@uwaterloo.ca

Ishan Baliyan
Department of Computer Science
University of Waterloo
Waterloo, ON, Canada
ibaliyan@uwaterloo.ca

Abstract

This paper introduces BodyMax AI, a machine learning system app that predicts body transformations after six months of training and fat loss. The approach leverages a fine-tuned version of the open-source FLUX-pro model, enhanced by integrating automated body segmentation with targeted muscle masking. Our research evaluates the efficacy of image-to-image translation models in generating realistic simulations of personalized physical transformations. Ultimately, this work aims to assess the accuracy of personalized body transformation predictions by using the novel approach of a fine-tuned image-to-image model which also uses targeted muscle masking to generate realistic outcomes.

1 Project Overview and Goals

The goal of the BodyMax AI project is to develop a machine learning app that predicts how a person's body might transform after six months of muscle training and fat loss. Users will upload a current body image, which will then be processed by our fine-tuned version of the open-source FLUX-pro model to generate a realistic simulation of the potential post-intervention body composition. This predictive visualization is designed to provide a personalized projection of physical transformation.

The primary research objective is to evaluate the efficacy of image-to-image translation models for predicting fitness-related body transformations. Specifically, we intend to explore the integration of body segmentation with targeted muscle masking, ensuring that the model focuses on modifying muscle regions while preserving other anatomical features.

Beyond its academic contributions, BodyMax AI will be deployed on the App Store, serving as a motivational tool for individuals on fitness journeys. The commercial release also offers an opportunity for iterative improvements based on user feedback. As we have previously built together an AI app with 40,000 downloads and $10,000 in profit (https://play.google.com/store/apps/details?id=com.wloo.airesume&hl=en), we believe this app also offers a possibility of commercial success.

2 Motivation and Novelty

Novel Innovation:
While image-to-image translation models (e.g., pix2pix, CycleGAN) have seen extensive use in image inpainting, their application in personal fitness visualization is largely unexplored. We will develop a tailored pipeline that first generates a body mask (to isolate muscle regions targeted for transformation) and then fine-tunes the FLUX-pro model to perform accurate inpainting and scaling.

Submitted to CS680, 2025 Winter. Do not distribute.

This combination of segmentation and transformation learning is novel in the context of fitness-related applications.

Real-world Impact:
Beyond its academic contribution, BodyMax AI is designed for consumer use — it is meant to make a real difference in people's lives. The app shows users a clear preview of how their bodies might change with regular exercise and healthy eating.

3 Model Evaluation Challenges and Current Progress

Current Progress
Early experiments with the FLUX-pro model have shown that it can perform image-to-image transformations on body images, albeit with outputs that are not realistic (the model alters the face and changes colour of skin). We have validated the concept of targeted muscle masking by manually drawing and applying a body mask to muscle regions. This approach has demonstrated that the FLUX-pro model is capable of generating improved results when it focuses on specific areas of the body.

Model Evaluation
To evaluate the accuracy of the model, we will use a combination of quantitative and qualitative methods. First, we will compare model-generated transformations against ground-truth images in the dataset, measuring structural similarity (SSIM) and pixel-wise differences. Second, we will manually evaluate side-by-side comparisons of real transformations and model-generated outputs, using an eye test to assess realism. Additionally, we plan to develop a metric that estimates body fat percentage changes based on key visual markers (e.g., muscle definition, waist circumference) and compare these estimates with known ground truth values from validated datasets.

4 Methodology and Feasibility

We plan to use publicly available fitness transformation datasets, including this dataset from Nexdata, supplemented by our own annotated images and those provided by our friends. A critical step in our pipeline is the automatic generation of a body mask from each input image, which isolates the target areas with muscle, that are intended for transformation. To achieve this, we will refine existing segmentation models for our specific application.

The FLUX-pro model will be fine-tuned using image pairs that simulate before-and-after transformations. We have already conducted preliminary experiments on personal images with promising results, as shown in the two generated examples (see Figure 1). We will buy cloud computing credits from Segmind to host and train the model. The costs will be roughly 4 cents per image once the model is trained.

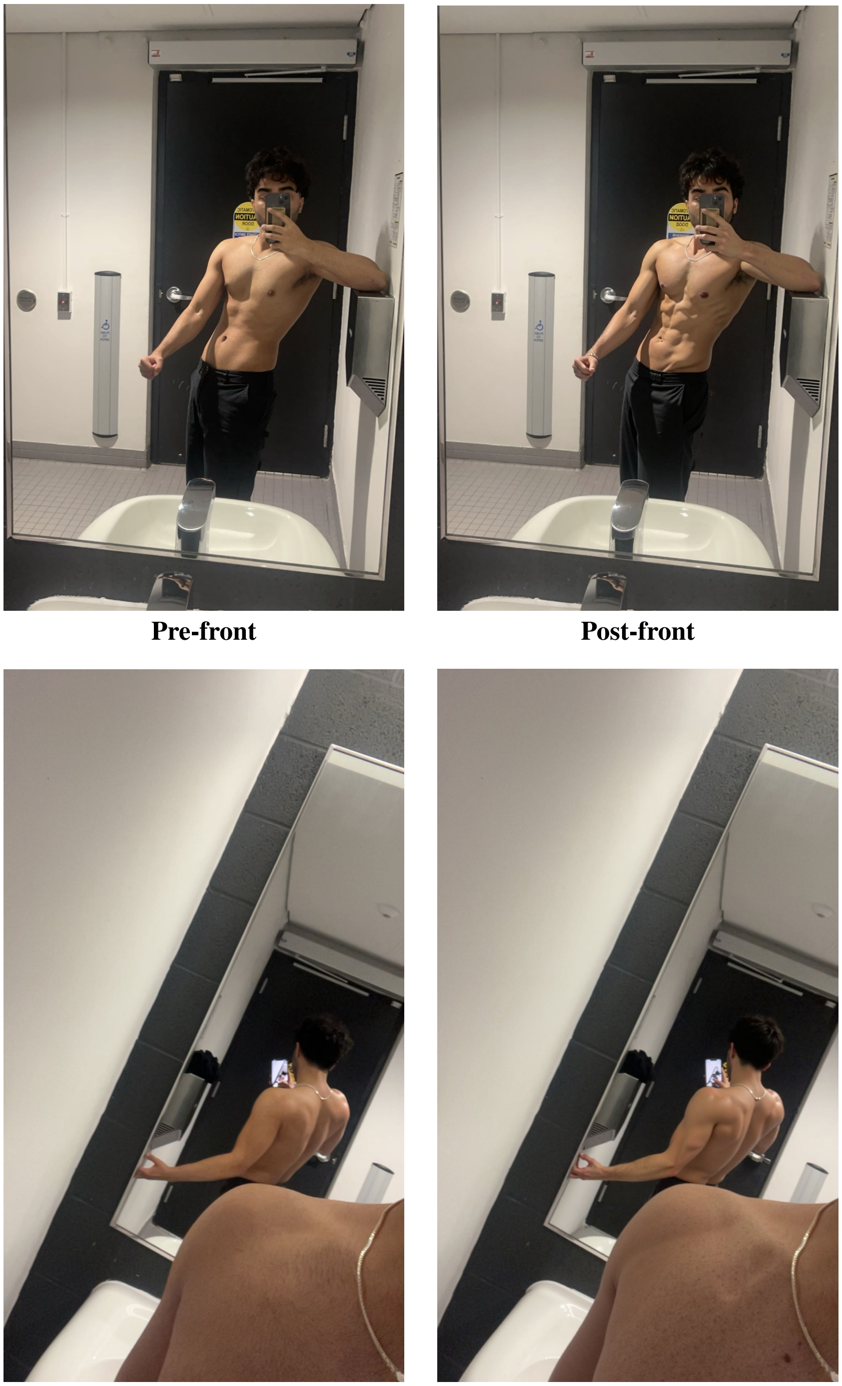
Given the project's complexity and our goal of launching a publicly available app, two people are needed for efficient development and integration. Below is our planned workload distribution.

Timeline and Individual Responsibilities:

- Weeks 1–4: Development of the body mask generation pipeline (Daniyal).
- Weeks 1–4: Fine-tuning of FLUX-pro with the body transformation dataset (Ishan).
- Weeks 4–7: Mobile app development and integration of the pipeline and custom diffusion model (both).
- Week 8: Final deployment and project wrap-up (both).

5 Conclusion

By fine-tuning the FLUX-pro model and introducing a muscle mask for personalized body transformation predictions, this project not only addresses an open research challenge but also promises tangible real-world impact.



Pre-front **Post-front**

Pre-back **Post-back**

Figure 1: Pre- and post-intervention body images (front/back).

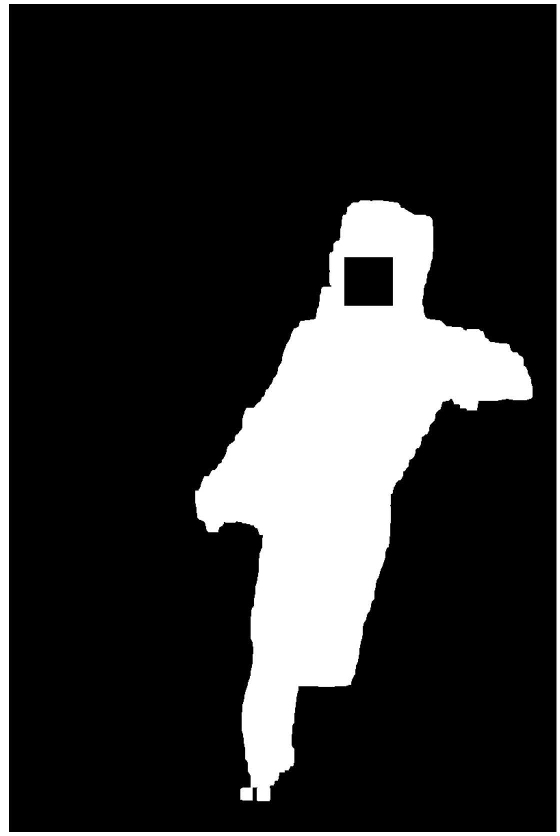


Figure 2: Manually built mask used for targeted areas.

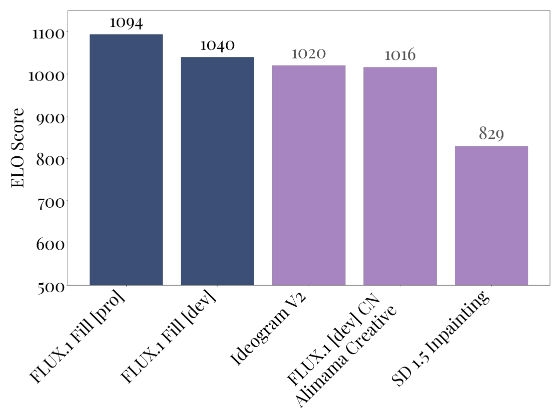


Figure 3: ELO score comparison among different inpainting models.

Acknowledgements

We thank our colleagues and friends from CS 480 at the University of Waterloo for their contributions, including Professor's Yao-Liang Yu for giving us an opportunity to work on a problem we care about and also his in-depth lectures and feedback, which have been essential in advancing this project.

References

Labs, B. F. (2023). "FLUX.1-Fill-dev on Hugging Face". Available at `https://huggingface.co/black-forest-labs/FLUX.1-Fill-dev`.

Lu, H., S. Szabados, and Y. Yu (2025). "Diffusion Models under Group Transformations". In: *International Conference on Artificial Intelligence and Statistics (AISTATS)*.

Mohammed, D. and I. Baliyan (2023). "Airesume: An AI-Powered Resume Builder". Accessed: 2025-02-13, `https://play.google.com/store/apps/details?id=com.wloo.airesume&hl=en`.

Nexdata.ai (2025). "Nexdata Fitness Transformation Dataset". Accessed: 2025-02-13, `https://www.nexdata.ai/datasets/computervision/1366`.

Segmind (2025). "Segmind Cloud Platform". Available at `https://www.segmind.com`.

Team, F.-p. (2024). "FLUX-pro: Open Source Image-to-Image Translation Model". Available at `https://github.com/flux-pro/flux-pro`.