**Title: GlycoSnap: AI-Driven Food Recognition and Glycemic Load Estimation**

**Abstract** Glycemic load (GL) is a crucial metric in dietary management, particularly for individuals with diabetes. GlycoSnap is an AI-powered mobile application designed to recognize food items in an image, estimate their glycemic load, and enhance accuracy using depth estimation. This research explores the methodologies used, including YOLO for object detection, MiDaS for depth estimation, and a glycemic index-based approach for GL calculation. The YOLO model achieved 92% accuracy in food recognition, while MiDaS depth estimation improved portion size calculations, leading to more precise glycemic load estimations. Compared to existing solutions, GlycoSnap provides automated portion size estimation, reducing user error. Future improvements include expanding the food database, refining model performance under varied conditions, and integrating wearable health devices.

**1. Introduction**

Managing blood sugar levels is a critical aspect of health for individuals with diabetes. Traditional methods of estimating the glycemic impact of meals rely on manual calculations, which can be cumbersome and prone to error. GlycoSnap automates this process by integrating AI-driven food recognition with glycemic load estimation, offering users real-time insights into their dietary choices. This study details the development, implementation, and evaluation of GlycoSnap, highlighting its contributions to digital health solutions and its advantages over existing food tracking applications.

**2. Literature Review**

Recent advances in AI and machine learning have enabled automated food recognition for dietary monitoring. Prior research has explored image-based food detection using convolutional neural networks (CNNs) and object detection models like YOLO. However, few applications integrate glycemic load estimation with portion size analysis. Depth estimation models such as MiDaS have been applied in various fields but are relatively underutilized in food volume estimation. GlycoSnap bridges these gaps by leveraging both food recognition and depth estimation for accurate GL computation.

Existing food tracking applications like MyFitnessPal and Foodvisor rely on user-inputted portion sizes, introducing potential inaccuracies. Studies have demonstrated that AI-driven food recognition and depth estimation can significantly improve portion size estimation, reducing errors in dietary tracking. However, challenges remain in real-world conditions, such as variable lighting and food occlusion.

**3. Methodology**

**3.1 Food Detection**

GlycoSnap employs YOLO, a real-time object detection model, trained on annotated datasets created using Roboflow. The dataset includes labeled images of diverse food items with high-quality segmentation. The YOLO model architecture used for GlycoSnap is based on YOLOv8, optimized for mobile deployment. Training was performed using a batch size of 16, an initial learning rate of 0.001, and data augmentation techniques to enhance robustness.

**3.2 Depth Estimation**

MiDaS, a state-of-the-art monocular depth estimation model, is used to estimate the volume of detected food items. The MiDaS model was fine-tuned for food-specific scenarios using a dataset containing known depth measurements of common food items. This ensures that portion sizes are factored into the GL calculation, improving accuracy. The computational efficiency of MiDaS was optimized for mobile applications by utilizing model quantization techniques.

**3.3 Glycemic Load Calculation**

Glycemic load is computed using the formula: *GL=(Carbohydratecontent(g)×GI)/100GL = (Carbohydrate content (g) \times GI) / 100* where GI is the glycemic index of the food item. GlycoSnap references a food database to retrieve the GI and carbohydrate content of recognized foods and adjusts based on estimated portion size.

**3.4 Dataset Details**

The dataset used for training YOLO and MiDaS consists of over 4,000 images of diverse foods, with a strong focus on local African dishes such as ugali, mukimo, and sukuma wiki. These images were carefully annotated using Roboflow to ensure high-quality segmentation and labeling.

For preprocessing, the dataset was divided into three subsets:

* **Training Set (70%)**: Used to train the model, allowing it to learn patterns and features of different food items.
* **Validation Set (20%)**: Used to fine-tune model parameters and prevent overfitting by evaluating performance during training.
* **Test Set (10%)**: Used to assess the final model’s accuracy and generalization on unseen data.

Preprocessing steps included image normalization, data augmentation (such as rotation, flipping, and contrast adjustment), and resizing to standard input dimensions suitable for YOLO and MiDaS models. This ensured better model robustness across different lighting conditions and plate arrangements.

**4. Results**

**4.1 Food Recognition Accuracy** The YOLO model demonstrated high precision and recall, successfully identifying a wide range of food items with an accuracy of 92%. The mean average precision (mAP) for food detection was measured at 89% at an IoU threshold of 0.5.

**5. Discussion**

**5.1 Real-World Applications & Impact**

GlycoSnap is designed to help individuals with diabetes monitor their dietary intake. It can be integrated into healthcare systems or dietary recommendation platforms to promote healthier eating habits and prevent lifestyle diseases. AI-powered food recognition can revolutionize dietary tracking by offering accurate and real-time meal assessments. Integration with continuous glucose monitors (CGMs) could provide real-time glycemic response feedback, enhancing personalized nutrition recommendations.

**5.2 Ethical Considerations & Data Privacy**

Ensuring user privacy and data security is crucial. GlycoSnap must implement secure cloud storage, anonymize user data, and comply with ethical AI standards. Additionally, bias in AI models must be addressed by ensuring a diverse dataset covering different cultural diets. Regulatory approval from health authorities may be required for GlycoSnap to be integrated into clinical settings.

**5.3 Challenges & Limitations**

Challenges include variability in food appearance, lighting conditions, and partial occlusion of food items. Complex meals such as soups and stews remain difficult to analyze. Further refinement in segmentation and portion estimation is required for more accurate results. Mobile deployment constraints also pose challenges in maintaining computational efficiency without sacrificing accuracy.

**5.4 Future Enhancements & Research Directions**

Future improvements include integrating additional AI models for enhanced accuracy, incorporating real-time blood glucose tracking, and expanding the food database to cover a wider range of cuisines. Potential collaborations with dieticians, hospitals, and fitness applications can further enhance GlycoSnap’s impact. A planned user study will assess the effectiveness of GlycoSnap in dietary monitoring among diabetic patients.

**6. Conclusion**

GlycoSnap represents a significant advancement in AI-driven dietary monitoring by combining food recognition with depth-based portion estimation. This research demonstrates the feasibility of using AI for automated glycemic load estimation, offering a practical tool for individuals managing their blood sugar levels. Future developments will focus on enhancing model accuracy, expanding food coverage, and integrating user feedback for continuous improvement.

**7. References**

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