# CS 5588: Data Science Capstone

# PoseRight - Project Progress Report

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## 1. Project Objectives and Features

Originally known as LymphFit, the project has evolved into PoseRight, which focuses on providing real-time posture analysis, movement guidance, and AI-driven personalized recommendations.
Since Assignment 1, I have expanded the scope to include a real-time comparison webapp, allowing users to compare their current posture against a reference standard.

Goal Refinements:

- Real-Time Comparison Webapp: A module for side-by-side posture comparisons.
- Enhanced Personalization: Integrating retrieval-augmented generative AI (RAG) for more context-aware recommendations.
- User-Focused Explainability: Using LLM-based interpretability methods (SHAP, LIME) to enhance feedback clarity.

Hands-on Learning Contributions:

- Deep Learning: Pose estimation using CNNs and exploration of Vision Transformers.
- Explainability with LLMs: Using SHAP, LIME, and GPT-based models for posture correction insights.
- Transformers & API Deployment: Integrated LoRA-tuned transformers and streamlined API integration.

Planned Improvements:

- Fine-tune GPT-based models with LoRA for personalized posture feedback.
- Implement LMMs for integrating text, images, and sensor data into the feedback pipeline.
- Scale the deployment using Docker and Kubernetes.

## 2. Literature Review and Novelty

Pose Estimation models have traditionally used CNN-based architectures (OpenPose, MediaPipe), while recent advances include Vision Transformers.

In generative AI, GPT-like models have shown promise in healthcare, but need domain adaptation.

Challenges:

- Accuracy in Noisy Environments: Pose detection can be affected by lighting, clothing, and occlusions.
- Computational Overhead: Real-time video processing and Transformer inference require optimization.
- Explainability: Users must trust AI recommendations.

Novelty Introduced:

- Real-Time Posture Comparison: Unlike static assessments, this feature enables dynamic tracking.
- RAG for Contextual AI Feedback: Retrieval-based AI ensures scientifically grounded advice.

## 3. Dataset and Preprocessing Updates

New Data Sources:

- Additional user-contributed posture videos.
- Professionally curated "golden standard" posture dataset.

Preprocessing Enhancements:

- Normalizing keypoints to a unified reference frame.
- Reducing noise in low-light or background-heavy images.
- Tokenizing user feedback for NLP-based recommendation tuning.

Challenges & Resolutions:

- Class Imbalance: Using data augmentation to address posture category distribution.
- Handling High Frame-Rate Data: Implementing memory-efficient buffering for real-time processing.

## 4. Technical Architecture and Implementation Progress

Architecture Evolution:

- Transitioned to a microservices-based system with modular services for detection, recommendation, and UI.

Data Flow & Processing:

1. User Input: Live video feed or uploaded images.
2. Pose Detection: Extracts keypoints using MediaPipe/CNN.
3. Real-Time Comparison: Compares detected posture with a reference image.
4. Recommendation Engine: Uses GPT-3.5 + RAG to provide AI-generated insights.
5. Front-End: Displays analysis and recommendations via Streamlit/Flask.

Current Model Performance:

- Pose Detection (PCK): ~85 percent in controlled settings, ~78 percent in real-world conditions.
- Text Generation (BLEU, ROUGE): ~0.45 BLEU, ~0.52 ROUGE-L.

## 5. Model Performance and Evaluation Metrics

Current Performance Metrics:

- Real-Time Latency: ~250ms/frame for semi-real-time feedback.
- Overfitting Prevention: Using data augmentation and domain adaptation.
- Future Enhancements: Testing Vision Transformers for improved robustness.

## 6. Fusion of AI Models

Current Fusion Strategy:

- Decision-Level Fusion: Pose detection output feeds into the recommendation engine.
- RAG for Personalized Recommendations: Fetches relevant guidance from curated physiotherapy sources.

Future Enhancements:

- Expand multi-modal analysis, integrating wearable sensor data.
- Optimize model inference time to ensure real-time usability.

## 7. Status of the Current Project

Completed Tasks:

- Developed real-time comparison webapp prototype.
- Integrated CNN-based detection with LLM-generated recommendations.
- Implemented a structured evaluation framework.

Challenges Encountered:

- Resource limitations for running AI models in real-time.
- Dataset bias toward specific postures; expanding dataset coverage.

Next Steps:

- Scale deployment using cloud-based GPU services.
- Extend user testing for fine-tuning model performance.

## 8. Expected Outcomes and Future Development

Final Deliverables:

1. A fully functional real-time posture correction system.
2. AI-driven recommendations with RAG-based knowledge retrieval.
3. Scalable and explainable AI-backed fitness assistance.

Upcoming Milestones:

- Full-scale deployment using Docker/Kubernetes.
- Expanding the AI explainability framework with user feedback loops.

## 9. Individual Contributions

Since I am the sole developer, all contributions are undertaken by me, Abhinav Kochar.

Contributions Include:

- Research & Development: Literature review, research synthesis.
- Data Processing: Collection, cleaning, augmentation.
- Model Training: Implemented CNN-based pose detection, fine-tuning of transformers.
- API & UI: Developed Flask endpoints and Streamlit-based real-time webapp.
- Evaluation & Deployment: Established performance metrics, optimized deployment with Docker.

Conclusion:

PoseRight has evolved into a comprehensive posture analysis tool, integrating deep learning, LLMs, and real-time user feedback.