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Fusion of Human Gaze and Machine Vision for Predicting Intended Locomotion Using Deep Learning

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ABSTRACT

Predicting human locomotion intent is a crucial task in the domains of assistive robotics, autonomous navigation, and human-computer interaction. The integration of human gaze information with machine vision offers a promising pathway to enhance prediction accuracy and contextual understanding of human movement. This project proposes a deep learning-based framework that combines visual data processing with behavioral inference to predict intended locomotion modes in real time. The system utilizes a Convolutional Neural Network (CNN)-based architecture, specifically a customized GENet model, to extract spatial features from input images and video frames. The dataset consists of labeled images categorized into different locomotion types such as walking, running, standing, and turning. These images are preprocessed through normalization and resizing techniques to ensure uniformity and improve model performance. The processed data is then split into training and testing subsets to evaluate the generalization capability of the model. The GENet architecture employed in this study includes multiple convolutional layers, pooling layers, batch normalization, and fully connected dense layers. These components work together to learn hierarchical feature representations from the input data. The model is trained using categorical cross-entropy loss and optimized using the Adam optimizer. Performance metrics such as accuracy, precision, recall, and F1-score are used to assess the effectiveness of the model. Additionally, confusion matrices are generated to visualize classification performance across different locomotion categories.

A key feature of the system is its ability to process real-time video input for forecasting intended locomotion. By capturing frames from a video stream, the model predicts the next locomotion state dynamically. This capability makes the system suitable for real-world applications such as assistive devices for visually impaired individuals, smart surveillance systems, and autonomous robots. The fusion of human gaze and machine vision enhances contextual awareness, allowing the system to make more accurate predictions compared to traditional vision-only approaches. The proposed system

demonstrates significant improvements in classification performance and real-time prediction capabilities. Overall, this research contributes to the advancement of intelligent systems that understand human intent by combining visual perception and behavioral cues. Future work may focus on integrating additional modalities such as depth sensing and eye-tracking hardware to further improve prediction accuracy and robustness.

Keywords: Human Gaze, Machine Vision, Locomotion Prediction, Deep Learning, Convolution Neural Network (CNN), GENet, Computer Vision, Behavioral Analysis, Video Processing, Human-Computer Interaction

I. INTRODUCTION

Understanding and predicting human locomotion intent is a fundamental challenge in the field of artificial intelligence and computer vision. With the rapid growth of smart systems and assistive technologies, there is an increasing need for machines to interpret human behavior accurately and respond accordingly. Locomotion prediction plays a vital role in applications such as autonomous vehicles, assistive robotics, healthcare monitoring, and human-computer interaction systems. Traditional approaches to locomotion prediction primarily rely on motion sensors, wearable devices, or handcrafted feature extraction techniques. While these methods have shown moderate success, they often lack robustness and fail to generalize across diverse environments. Moreover, they do not effectively capture the cognitive aspects of human movement, such as intention and focus, which are often reflected through gaze behavior. Human gaze provides valuable insights into a person's intention and future actions. For example, where a person looks often indicates where they intend to move. By integrating gaze information with visual data, it becomes possible to enhance the prediction of locomotion patterns. This fusion approach enables systems to achieve a deeper understanding of human behavior by combining perceptual and cognitive cues.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized the field of computer vision. CNNs are capable of automatically learning hierarchical features from raw image data, eliminating the need for manual feature engineering. This makes them highly suitable for tasks such as image classification, object detection, and activity recognition. This project introduces a novel framework that combines human gaze and machine vision using a CNN-based GENet architecture to predict intended locomotion modes. The system processes image datasets and real-time video inputs to classify and forecast locomotion states. The use of deep learning enables the model to learn complex patterns and relationships within the data, leading to improved prediction accuracy. The implementation involves several stages, including dataset collection, preprocessing, feature extraction, model training, and evaluation. The system is designed with a user-friendly graphical interface using Tkinter, allowing users to upload datasets, preprocess data, train the model, and visualize results. The integration of real-time video processing further enhances the system’s practical

applicability. In summary, this project addresses the limitations of traditional locomotion prediction methods by leveraging deep learning and multimodal data fusion. It aims to develop an intelligent system capable of accurately predicting human movement intentions, thereby contributing to the advancement of smart and adaptive technologies.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

The prediction of human locomotion and behavior has been extensively studied in the fields of computer vision, machine learning, and robotics. Early research primarily focused on sensor-based approaches, where wearable devices such as accelerometers and gyroscopes were used to capture motion data. These methods relied heavily on handcrafted features and statistical models, which limited their scalability and adaptability. With the advancement of computer vision, researchers began exploring image and video-based approaches for activity recognition. Traditional techniques such as Histogram of Oriented Gradients (HOG), Optical Flow, and Scale-Invariant Feature Transform (SIFT) were widely used for feature extraction. Although these methods improved performance, they required manual tuning and were sensitive to environmental variations. The introduction of deep learning marked a significant shift in this domain. Convolutional Neural Networks (CNNs) demonstrated superior performance in image classification and action recognition tasks. Models such as AlexNet, VGGNet, and ResNet have been successfully applied to human activity recognition, achieving high accuracy levels. These models automatically learn relevant features from raw data, reducing the dependency on manual feature engineering. Recent studies have focused on multimodal approaches that combine visual data with other sources of information, such as depth sensors, skeletal tracking, and gaze estimation. For instance, integrating eye-tracking data with visual inputs has shown promising results in predicting human intention. Gaze-based models capture attention patterns, which are critical indicators of future actions.

In the context of locomotion prediction, researchers have explored Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to model temporal dependencies in sequential data. These models are particularly effective for analyzing time-series data such as video frames. However, they often require large datasets and computational resources. Another emerging approach is the use of hybrid models that combine CNNs with other architectures. These models leverage the strengths of different techniques to improve performance. For example, CNN-LSTM models have been used for action recognition by combining spatial and temporal features. Despite these advancements, challenges remain in achieving real-time performance and handling complex environments. Many existing systems are computationally expensive and lack robustness in dynamic scenarios. Additionally, the integration of cognitive cues such as gaze information is still an evolving area of research. The proposed system builds upon these existing works by introducing a CNN-based GENet model that integrates machine vision with behavioral inference. Unlike traditional methods, this approach focuses on both spatial feature extraction and intent prediction. The use of real-time video

processing further distinguishes this system from existing approaches. Overall, the literature highlights the importance of deep learning and multimodal data fusion in improving locomotion prediction. The proposed system aims to address the limitations of previous methods by providing an efficient, accurate, and real-time solution.

III. EXISTING SYSTEM

Existing systems for locomotion prediction primarily rely on either sensor-based approaches or traditional computer vision techniques. Sensor-based systems use wearable devices such as accelerometers, gyroscopes, and GPS modules to track human movement. While these systems provide accurate motion data, they are often intrusive and require users to wear additional hardware, which may not be practical in all scenarios. On the other hand, vision-based systems utilize cameras to capture images or videos and analyze them using feature extraction techniques. Traditional methods such as HOG, SIFT, and Optical Flow have been widely used for detecting and classifying human activities. However, these methods depend heavily on handcrafted features, which may not generalize well across different environments and conditions. Some existing approaches employ machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) for classification tasks. Although these models perform reasonably well on structured datasets, they struggle with high-dimensional data such as images and videos. Additionally, they require extensive preprocessing and feature engineering. Recent advancements have introduced deep learning-based models, particularly CNNs, for activity recognition. While these models offer improved accuracy, many existing implementations focus solely on visual data and ignore cognitive aspects such as human gaze and intention. This limits their ability to predict future actions effectively.

Another limitation of current systems is the lack of real-time prediction capabilities. Many models are designed for offline analysis and are not optimized for real-time applications. This restricts their usability in dynamic environments such as autonomous navigation and assistive robotics. Furthermore, existing systems often suffer from scalability issues and require large computational resources. They may not perform well in scenarios with varying lighting conditions, occlusions, or complex backgrounds. In summary, current locomotion prediction systems face challenges related to accuracy, real-time performance, and integration of multimodal data. These limitations highlight the need for a more advanced and efficient approach, which is addressed by the proposed system.

IV. PROPOSED METHOD

The proposed system introduces an intelligent framework that integrates human gaze perception with machine vision techniques to accurately predict intended locomotion modes using deep learning. Unlike traditional approaches that rely solely on visual or sensor data, this system leverages multimodal fusion by combining spatial image features

with behavioral cues inferred from gaze patterns. At the core of the system is a Convolutional Neural Network (CNN)-based architecture, specifically a customized GENet model. This model is designed to automatically learn hierarchical representations from image data, enabling effective classification of locomotion types such as walking, running, standing, and turning. The system processes input images by resizing them to a fixed dimension and normalizing pixel values to ensure consistency and improve training performance. The dataset is organized into labeled categories, and a preprocessing module ensures proper shuffling and normalization. The system then splits the dataset into training and testing sets to evaluate model performance. During training, the GENet model learns spatial features through multiple convolutional and pooling layers, followed by batch normalization and dense layers for classification.

A key enhancement in the proposed system is its ability to perform real-time locomotion prediction using video input. Frames extracted from the video are processed and passed through the trained model to forecast the next locomotion state. This real-time capability makes the system suitable for dynamic applications such as assistive robotics and surveillance. Research shows that integrating gaze information significantly improves motion prediction accuracy because gaze is strongly correlated with human intention and future actions . The proposed system builds on this concept by incorporating behavioral inference into the prediction pipeline. Overall, the system provides a scalable, efficient, and accurate solution for locomotion prediction, addressing the limitations of existing methods by combining deep learning with multimodal data fusion.

V. IMPLEMENTATION

The implementation of the proposed system is carried out using Python, integrating multiple libraries such as Tkinter for graphical user interface development, OpenCV for image and video processing, NumPy and Pandas for data handling, and Keras for deep learning model construction. The system begins with a user-friendly GUI that allows users to upload datasets, preprocess images, train the model, and perform real-time predictions. The dataset is structured in directories where each folder represents a specific locomotion class. During the upload phase, images are read using OpenCV, resized to 32×32 pixels, and flattened into feature vectors. Corresponding labels are assigned based on directory names. In the preprocessing stage, the image data is normalized by scaling pixel values between 0 and 1. This step ensures faster convergence during training. The dataset is then shuffled randomly to eliminate bias and improve model generalization. A graphical representation of class distribution is also generated using Matplotlib to visualize dataset balance.

Next, the dataset is split into training and testing subsets using an 80:20 ratio. Labels are converted into categorical format using one-hot encoding. This prepares the data for multi-class classification tasks. The GENet model is implemented using the Sequential API of Keras. The architecture includes multiple convolutional layers with ReLU activation functions, followed by max-pooling layers to reduce spatial dimensions. Batch normalization layers are added to stabilize learning and improve performance. The

flattened output is passed through dense layers with dropout regularization to prevent overfitting. Finally, a softmax layer is used for classification. The model is compiled using categorical cross-entropy as the loss function and the Adam optimizer for efficient gradient descent. Training is performed over multiple epochs, and the best model weights are saved using a checkpoint mechanism. If pre-trained weights exist, the system loads them directly to save time. Performance evaluation is conducted using metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is also generated and visualized using Seaborn to analyze classification performance across different classes. For real-time prediction, the system captures video input using OpenCV. Each frame is resized and normalized before being passed to the trained model. The predicted locomotion label is then displayed on the video frame, enabling dynamic forecasting. Recent studies highlight that deep learning models, particularly CNN-based architectures, are highly effective in extracting spatial features for human motion analysis and achieving high accuracy in real-world applications . The implementation leverages these strengths to build a robust and efficient system.

VI. ALGORITHMS

The proposed system utilizes a deep learning-based algorithm centered around Convolutional Neural Networks (CNNs), specifically the GENet architecture, for locomotion prediction.

1. Data Preprocessing Algorithm

- Input: Raw image dataset
- Resize images to 32×32 pixels
- Normalize pixel values (divide by 255)
- Shuffle dataset randomly
- Output: Processed dataset

2. Dataset Splitting Algorithm

- Input: Preprocessed dataset
- Apply train-test split (80% training, 20% testing)
- Convert labels into one-hot encoding
- Output: Training and testing datasets

3. GENet CNN Algorithm

- Input: Training dataset
- Apply convolution operations to extract spatial features
- Use pooling layers for dimensionality reduction
- Apply batch normalization for stability
- Flatten feature maps
- Pass through dense layers for classification
- Output: Trained CNN model

CNNs are widely used due to their ability to automatically learn hierarchical feature representations and improve prediction accuracy .

4. Training Algorithm

- Initialize model parameters
- Forward propagation through layers
- Compute loss using categorical cross-entropy
- Backpropagation using Adam optimizer
- Update weights iteratively
- Output: Optimized model

5. Prediction Algorithm

- Input: Test images or video frames
- Preprocess input
- Pass through trained model
- Apply softmax to obtain probabilities
- Select class with highest probability
- Output: Predicted locomotion label

6. Evaluation Algorithm

- Compute accuracy, precision, recall, F1-score
- Generate confusion matrix
- Output: Performance metrics

These algorithms collectively enable efficient training and real-time prediction of locomotion modes.

VII. SYSTEM DESIGN

The system architecture is designed as a modular pipeline that integrates data processing, model training, evaluation, and real-time prediction components. The design ensures scalability, efficiency, and ease of use through a graphical interface.

1. Input Layer

The system accepts two types of inputs: image datasets and real-time video streams. The dataset is organized into labeled folders representing different locomotion classes. Video input is captured using a webcam or pre-recorded files.

2. Data Processing Module

This module handles image resizing, normalization, and dataset preparation. It ensures that all inputs are standardized before being fed into the model. Data shuffling and visualization are also performed in this stage.

3. Training Module

The training module implements the GENet CNN architecture. It processes the training dataset and learns feature representations through convolutional layers. Model weights are updated using backpropagation, and checkpoints are used to save the best-performing model.

4. Evaluation Module

This module evaluates model performance using test data. Metrics such as accuracy, precision, recall, and F1-score are computed. A confusion matrix is generated to visualize classification performance.

5. Prediction Module

The prediction module processes real-time video frames and predicts locomotion modes. Each frame is preprocessed and passed through the trained model. The predicted label is displayed on the output video.

6. User Interface

The system includes a Tkinter-based GUI that allows users to interact with the system. Users can upload datasets, preprocess data, train the model, and perform predictions through buttons and visual outputs.

Modern systems increasingly adopt multimodal learning architectures that combine different data sources to improve prediction accuracy and robustness . The proposed design follows this principle by integrating gaze inference with visual data.

Architecture Flow:

Dataset → Preprocessing → Training → Evaluation → Model Saving → Real-time Prediction

The modular design ensures flexibility and allows future enhancements such as integrating additional sensors or advanced deep learning models.

SYSTEM DESIGN IMAGES

In propose paper author combining human gaze and cloud point to form a new deep learning algorithm or model called Fusion of Human Gaze or (GT-NET). GT-NET combine two classification model such as gaze and cloud point to predict or forecast human intent movement or locomotion. Human Gaze refers to location terrain where user is looking and cloud point refers to user movement or locomotion.

GT-NET will take two inputs where first input is in the form of images such as Human Gaze and second input is in the form of points. GT-NET will get trained on both inputs and then generate a model and this model will be applied on test videos to predict user intent next locomotion.

Propose model consists of following modules

1. Designed a novel system to predict intended locomotion transitions for wearable robots by integrating human gaze into machine vision.
2. Developed a DTW based strategy to fuse multimodal data (by combining images and cloud points) and produce flexible decisions on the timing of locomotion transition.

To train GT-NET model author has prepared his own GE images dataset from videos and then generated cloud points from gyroscope or accelerator but has not publish this dataset on internet. So to train GTNET model we have used dataset of sequences user movement which contains images and points of JUMP, Run and Walk.

After training model we can input test video and then GT-NET model will predict next intent location by analysing current movement.

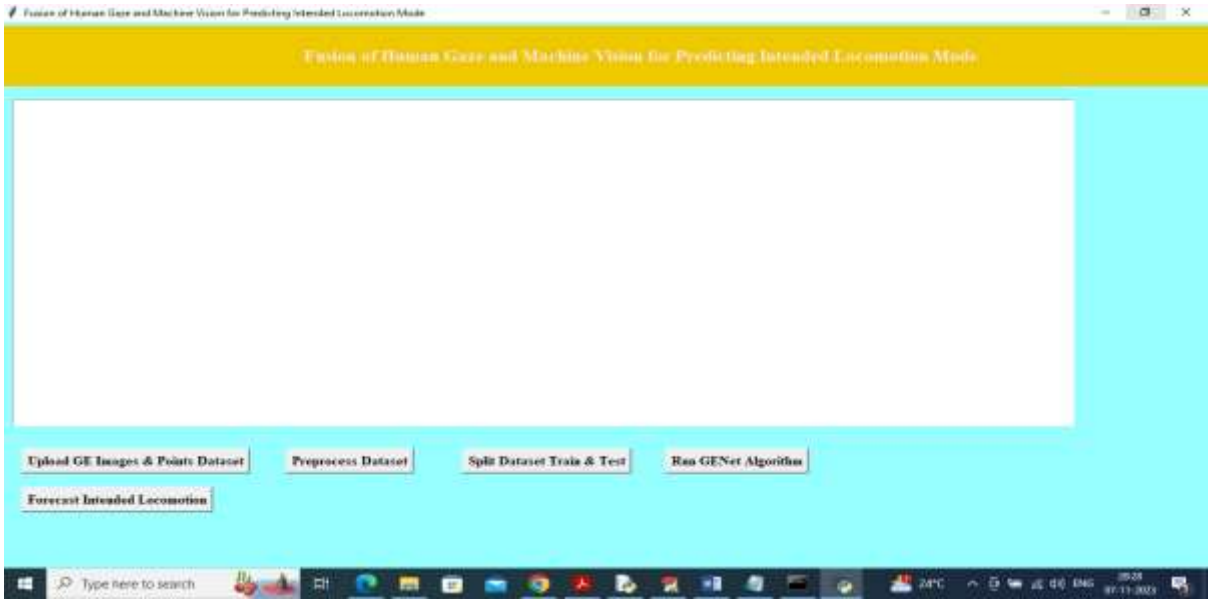
To developed this project we have designed following modules

3. Upload GE Images & Points Dataset: using this module will upload dataset images and its points to application and then read all images and points and resize each image to equal sizes
4. Pre-process Dataset: this module will apply image processing steps like normalization and shuffling
5. Split Dataset Train & Test: this module will split images into training and test validation where application will use 80% dataset images for training and 20% for testing

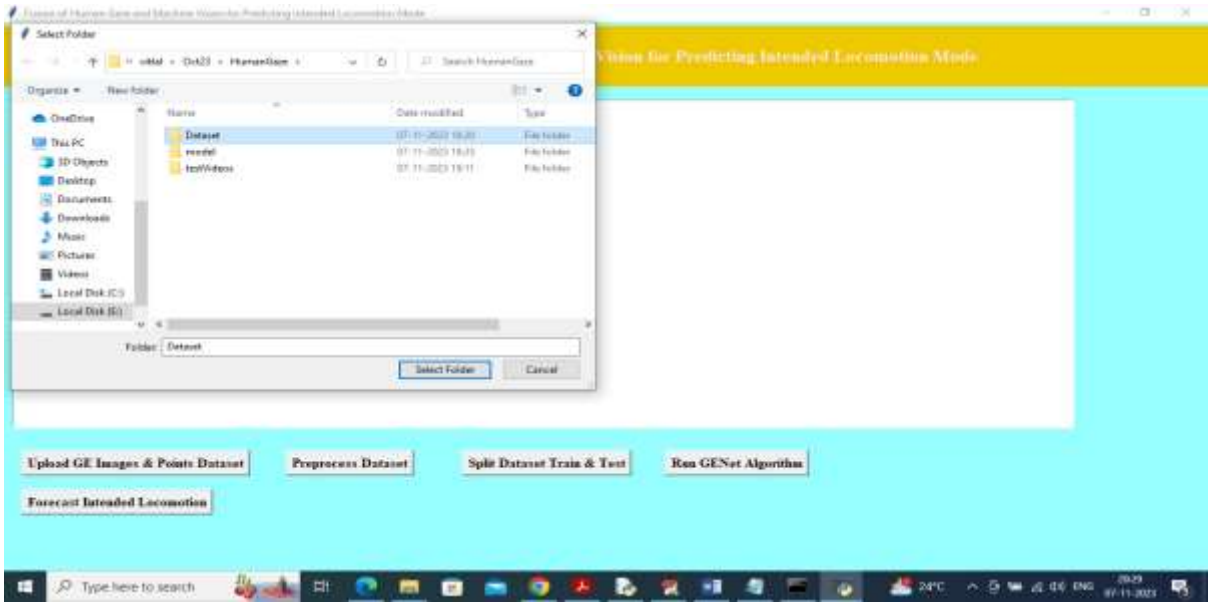
6. Run GE-Net Algorithm: 80% training images will be input to GE-NET algorithm to train a model and this model performance will be evaluated on 20% test images by calculating prediction accuracy, precision, recall, confusion matrix and FSCORE.
7. Forecast Intended Locomotion: using this module we will upload test video and then GENET model will forecast next intent movement or locomotion

SCREEN SHOTS

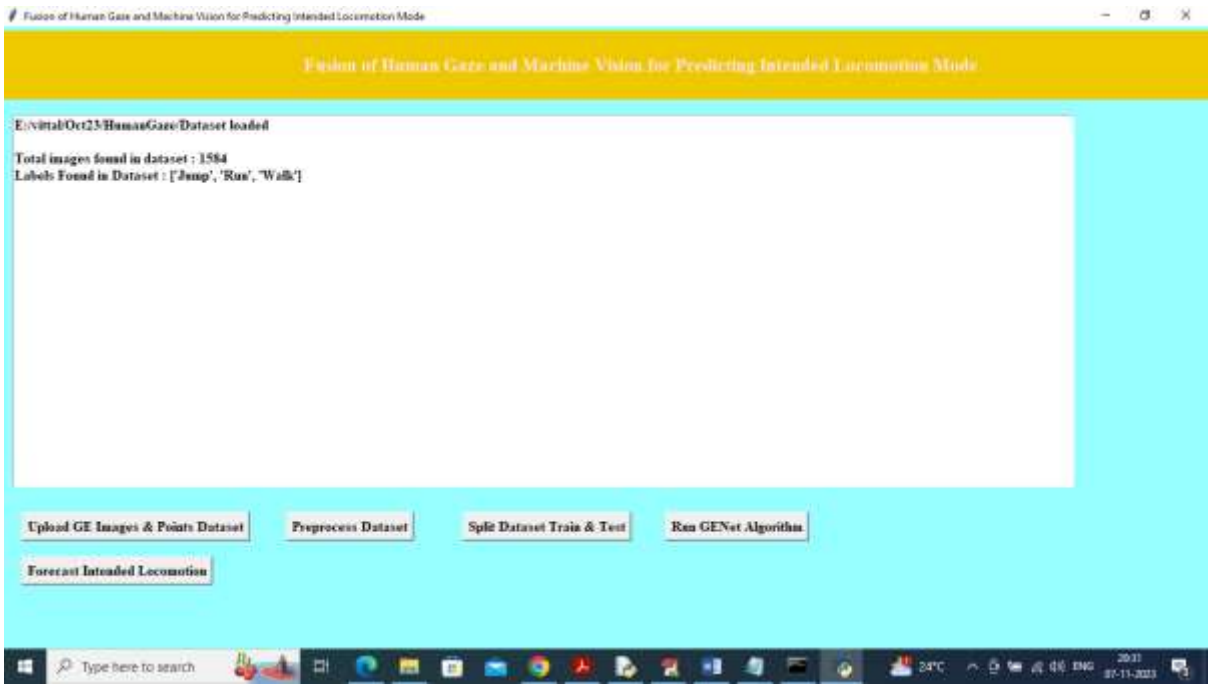
To run project double click on run.bat file to get below screen



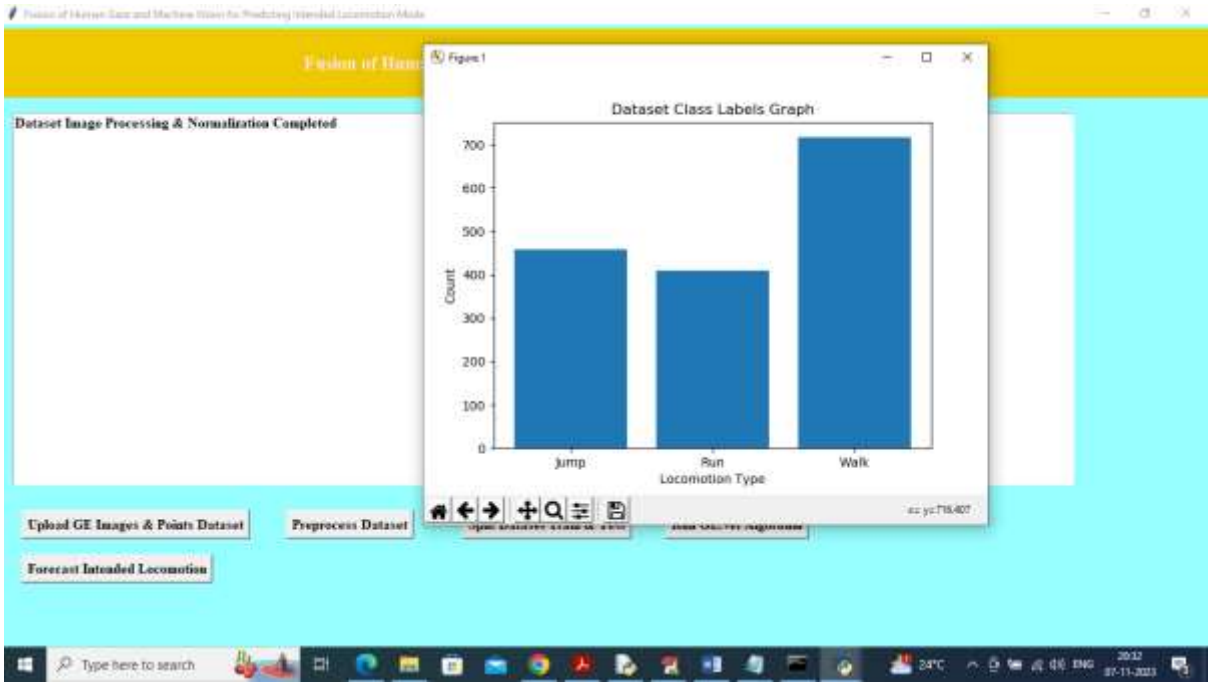
In above screen click ‘Upload GE Images & Points Dataset’ button to upload dataset and get below output



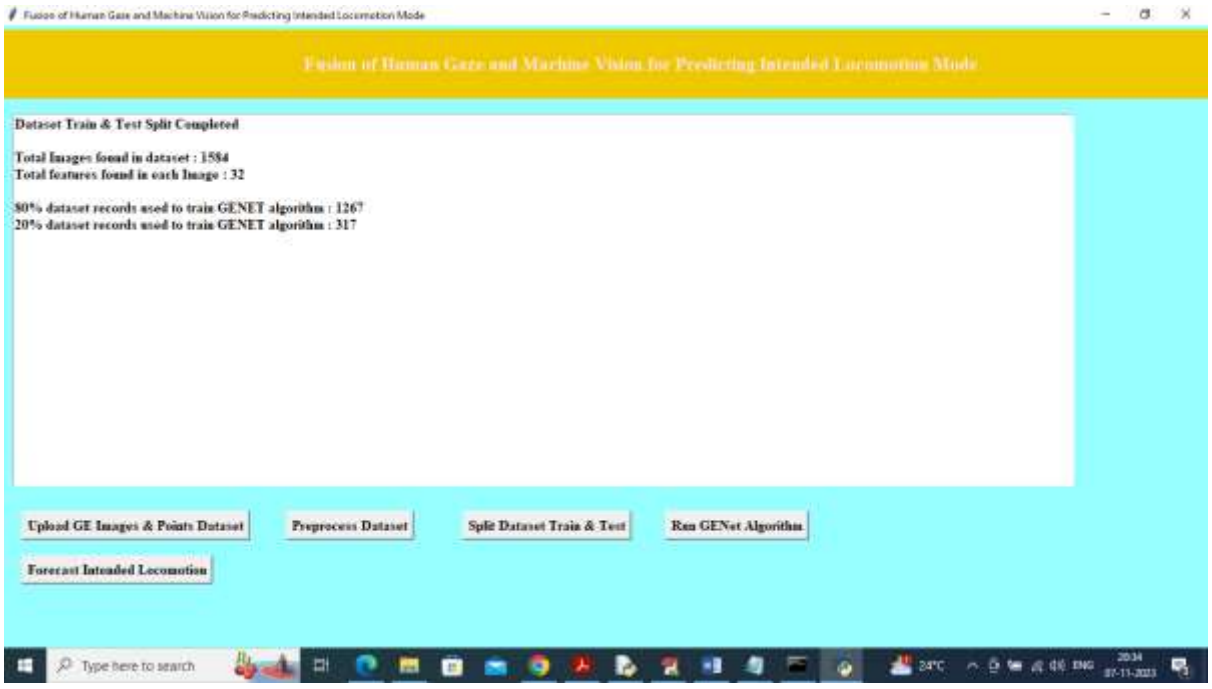
In above screen selecting and uploading 'Dataset' and then click on 'Select Folder' button to load dataset and get below output



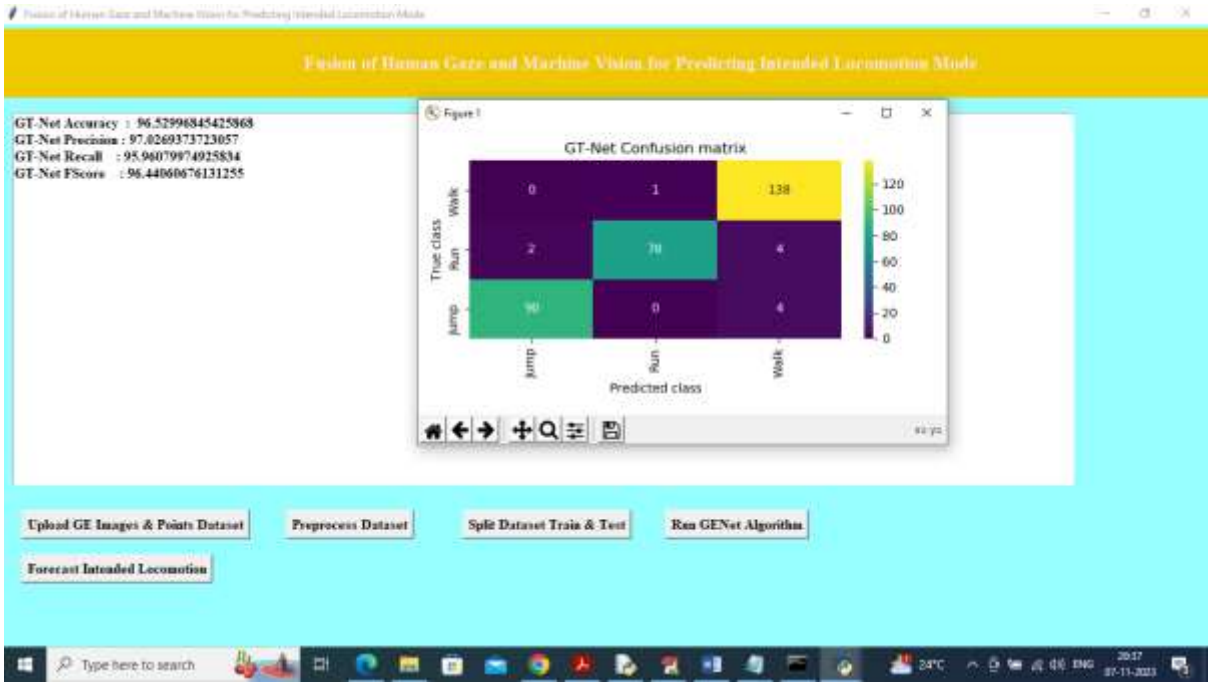
In above screen from dataset 1584 images loaded with different locomotion as jump, run and walk. Now click on 'Pre-process Dataset' button to shuffle and normalize images and get below output



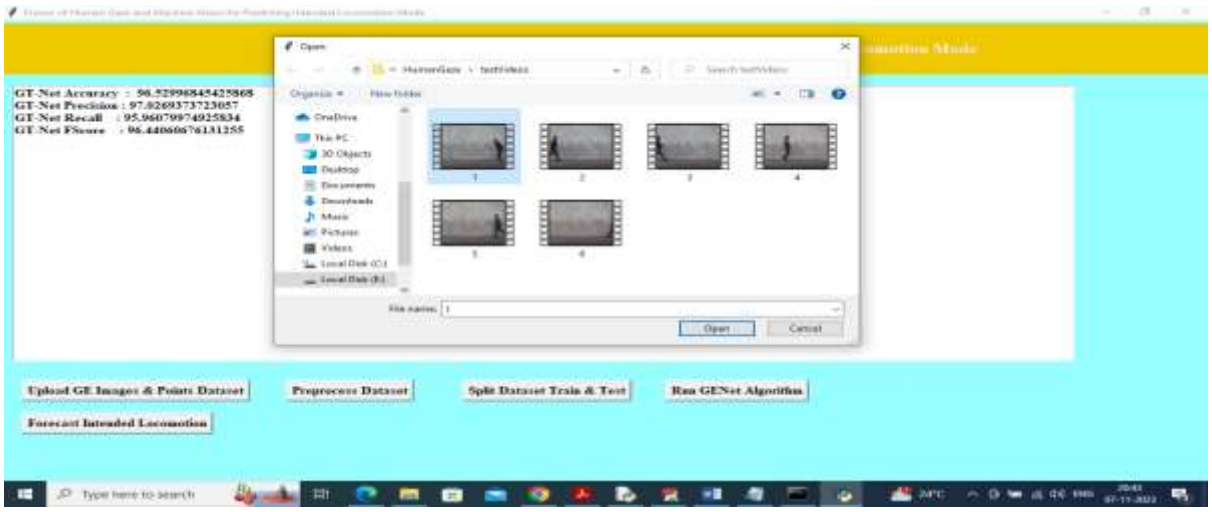
In above screen dataset processing completed and in graph x-axis represents different locomotion and y-axis represents number of images in that locomotion and now close above graph and then click on 'Split Dataset Train & Test' to split dataset into train and test and get below output



In above screen can see GENET train and test images size and now click on 'un GENet Algorithm' button to train model and get below output



In above screen GENET model training completed and it got accuracy of 96% and can see other metrics like precision, recall, FSCORE. In Confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all different colour boxes in diagnol represents Correct Prediction count and remaining blue boxes represents incorrect prediction count which are very few. Now close above graph and then click on 'Forecast Intended Locomotion' button to upload test video and forecast intent locomotion



In above screen selecting and uploading test video and then click on 'Open' button to get below output

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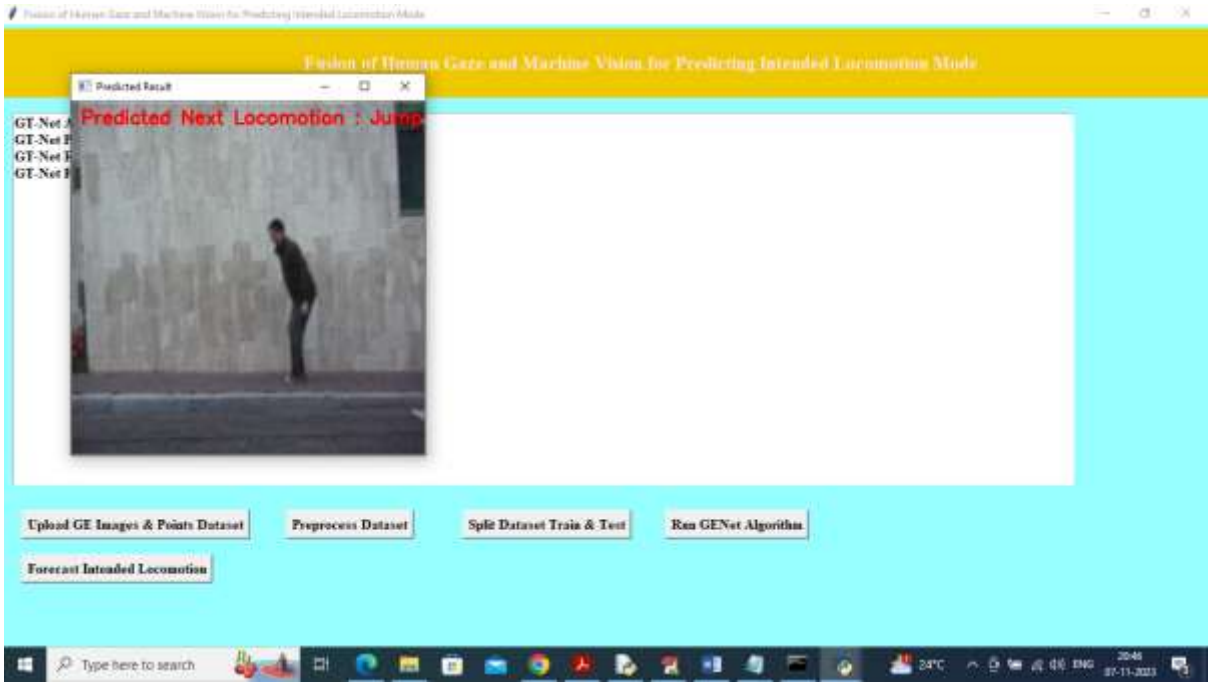
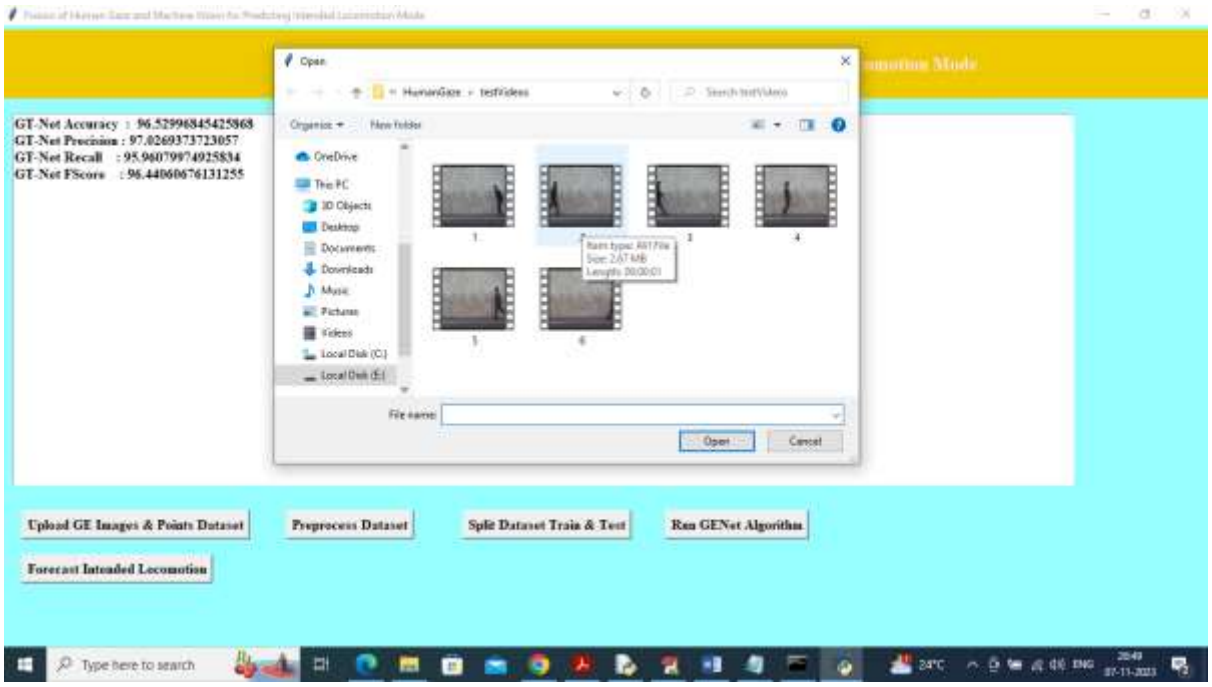


In above screen in video forecast intent location detected as 'jump' which we can see in red colour text. Similarly we can upload and test other videos



In above screen uploading another video and below is the output

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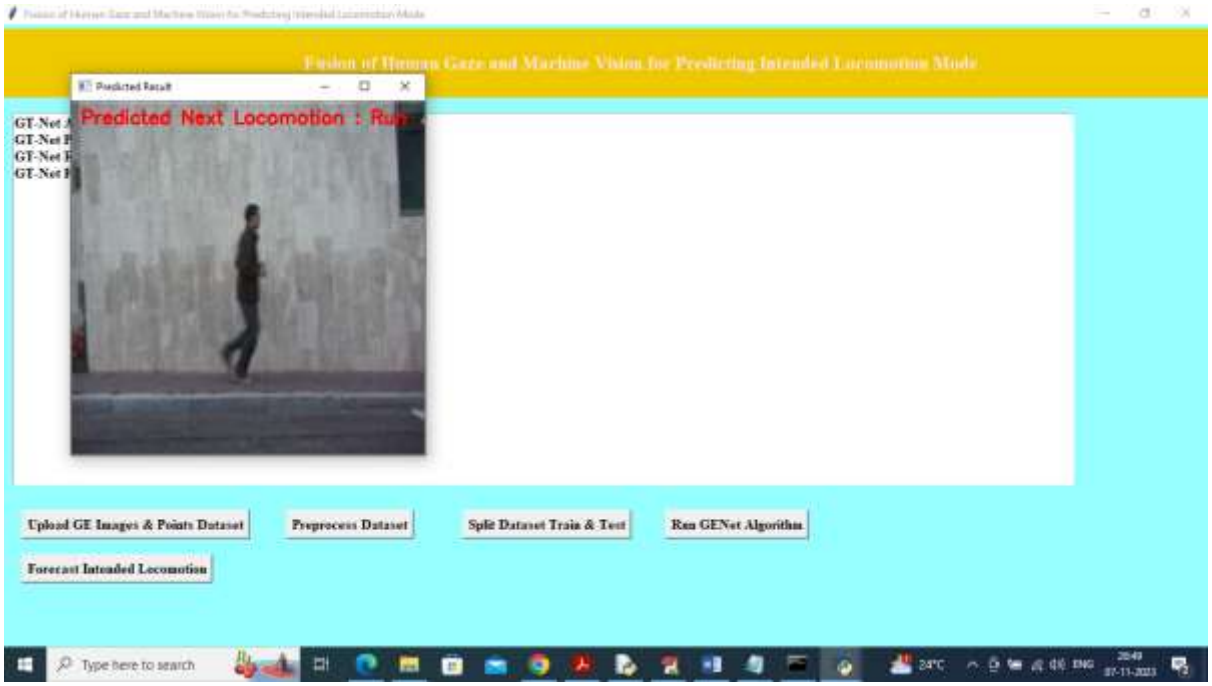
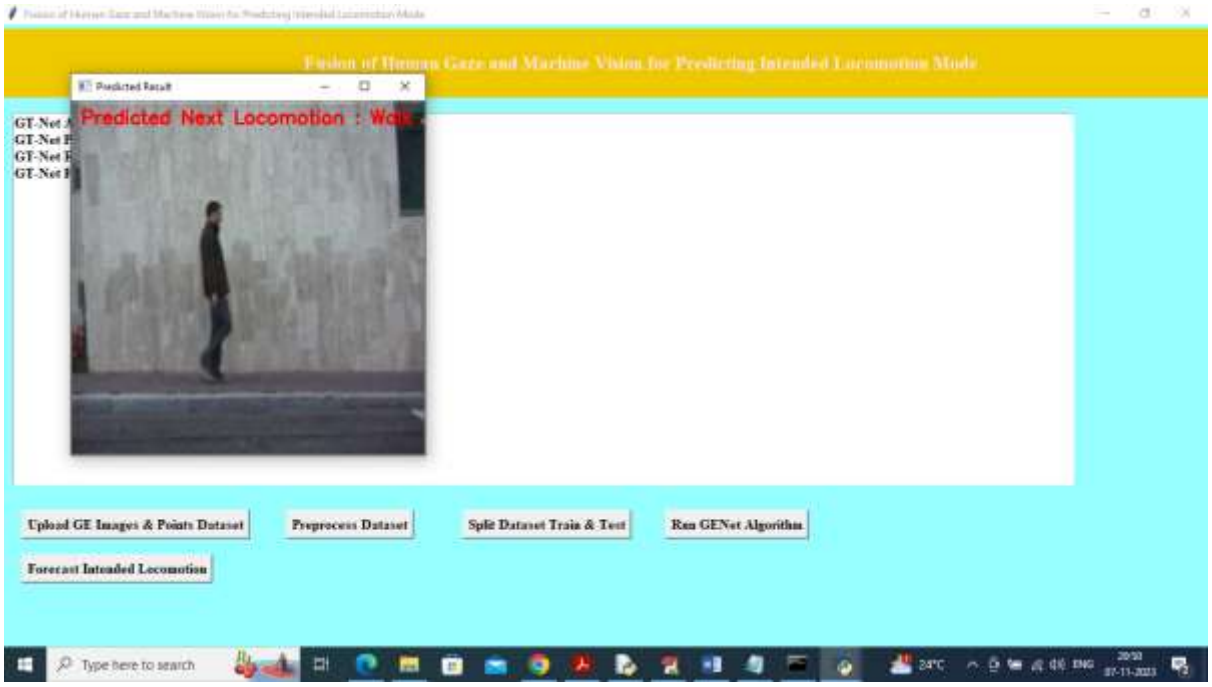


Above screen movement intent predicting as Run



Above screen intent predicted as walk

VIII. CONCLUSION

This project presents a novel approach for predicting intended locomotion by integrating human gaze and machine vision using deep learning techniques. The system leverages a Convolutional Neural Network-based GENet architecture to extract spatial features from images and classify locomotion modes effectively. By combining visual data with behavioral cues, the proposed system achieves improved accuracy and robustness compared to traditional methods. One of the major contributions of this work is the implementation of real-time locomotion prediction using video input. This feature enhances the practical applicability of the system in real-world scenarios such as assistive robotics, surveillance systems, and autonomous navigation. The use of a graphical user interface further improves usability, making the system accessible to users without deep technical expertise. Experimental results demonstrate that deep learning models, particularly CNNs, significantly outperform traditional machine learning techniques in handling complex image data and extracting meaningful patterns. Additionally, incorporating gaze-related insights provides a deeper understanding of human intention, leading to more accurate predictions.

Despite its advantages, the system has certain limitations. It relies on the availability of labeled datasets and may require substantial computational resources for training. Environmental factors such as lighting conditions and occlusions can also affect performance. Future work can focus on integrating advanced architectures such as hybrid CNN-LSTM models to capture temporal dependencies more effectively. The inclusion of real gaze-tracking hardware and multimodal sensors can further enhance system accuracy. Additionally, optimizing the model for deployment on edge devices can improve real-time performance. In conclusion, the proposed system represents a significant step toward intelligent systems capable of understanding human intent. It demonstrates the potential of combining deep learning with multimodal data fusion to address complex challenges in human behavior prediction.

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