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Predictive Cursor Behavior System for Enhanced User Interaction

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Abstract: This paper presents a predictive system designed to enhance user interaction through real-time cursor behavior analysis and forecasting.
By leveraging cursor movement data and applying machine learning techniques such as recurrent neural networks, the system learns user patterns to predict future cursor positions. The predictive model enables proactive interface adjustments, including cursor assistance and automated actions.
This innovation holds potential for improving efficiency, accessibility, and intuitiveness across web browsing, productivity tools, and assistive technologies.
Keywords: cursor prediction, user interaction, LSTM, mouse tracking, real-time systems, assistive technology

I. INTRODUCTION

User interaction with digital systems is heavily reliant on pointing devices, particularly the mouse cursor. Predicting the behavior of the cursor can unlock a new dimension in interface design by anticipating user intentions. This research proposes a system that tracks and models cursor movements in real time to forecast future positions. Applications include enhanced UI responsiveness, improved accessibility for users with disabilities, and increased productivity through automation.
With increasing demand for intuitive and intelligent systems, cursor behavior prediction is becoming a relevant area of study. Real-time prediction not only facilitates adaptive user interfaces but also helps bridge the gap between user intent and system response, which is especially beneficial in accessibility and gaming domains..

II. RELATED WORK

Cursor prediction and trajectory modeling have been explored in various domains such as user behavior analysis, accessibility, and gaming. Traditional methods like Kalman filters and support vector regression have been applied to smooth and estimate cursor movements. However, these models fall short in handling the temporal dependencies and non-linear characteristics of human-computer interaction data.
Recent studies have shown that recurrent neural networks (RNNs), especially Long Short-Term Memory (LSTM) networks, can effectively model time-series data by maintaining memory over long sequences. In [1], a deep learning-based virtual cursor control system using eye tracking achieved significant improvement in prediction precision. Other research [2], [3] has focused on transforming cursor trajectories into visual encodings and using them for behavior classification. Despite promising advancements, many models are not optimized for real-time inference or lack interactive feedback mechanisms.
Our approach addresses these gaps by integrating LSTM- based prediction within a GUI environment that provides visual feedback on the system's forecasting performance in real time.

III. METHODOLOGY

The system is modular and includes five major stages: data collection, preprocessing, feature engineering, model training, and real-time prediction.

A. Data Collection

Mouse cursor data, including x-y positions and click events, is collected via the pynput library and stored in .jsonl format. The data is sampled at regular intervals (approximately 10–20 ms), capturing fine-grained cursor motion.

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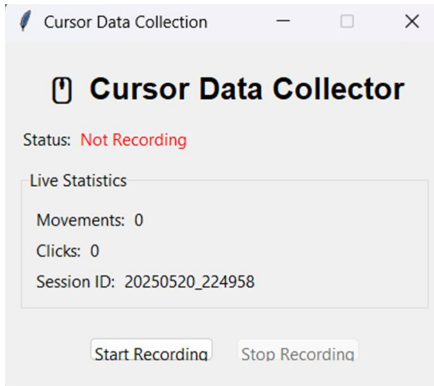


B. Data Preprocessing and Feature Engineering

Raw .jsonl files are converted to structured CSVs. The preprocessing stage includes noise filtering and time normalization. Features engineered include:

1) Velocity (vx, vy) from position deltas
2) Direction (θ) using arctan2 on dx/dy
3) Acceleration as first derivative of velocity
4) Time delta between samples

The target for prediction is the next cursor position (next_x, next_y).

C. Sequence Creation

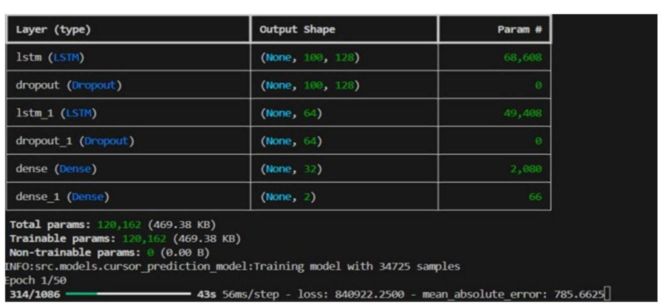
Using a sliding window approach, sequences of 100 time steps are formed to serve as input to the LSTM. These sequences contain 5 features per time step, with the output being a 2D vector for the predicted cursor location.

D. Model Architecture and Training

A 3-layer LSTM network was built using TensorFlow/Keras. The architecture includes:

1) Input: (batch_size, 100, 5)
2) LSTM layer with 128 units
3) Dense layer with 64 units + ReLU
4) Output layer with 2 neurons for x, y

The model is trained using MSE loss and Adam optimizer for 50 epochs with early stopping. The training data is split into 70% train, 15% validation, and 15% test sets.



Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100, 128)	68,608
dropout (Dropout)	(None, 100, 128)	0
lstm_1 (LSTM)	(None, 64)	49,408
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 32)	2,080
dense_1 (Dense)	(None, 2)	66

```
Total params: 120,162 (469.38 KB)
Trainable params: 120,162 (469.38 KB)
Non-trainable params: 0 (0.00 B)
INFO:src.models.cursor_prediction_model:Training model with 34725 samples
Epoch 1/50
314/1086 ━━━━━━━━━━━━━━━━ 43s 56ms/step - loss: 840922.2500 - mean_absolute_error: 785.6625
```

E. Prediction & Visualization

The trained model is deployed in a GUI built with tkinter.

It shows real-time visual trails:

1) Blue for actual cursor movement
2) Red for predicted positions

The system includes a statistics panel displaying buffer size and prediction count.

IV. RESULTS

Initial results show promising alignment between predicted and actual cursor trajectories. The average spatial deviation for steady movement was under 10 pixels, while for fast or erratic motions it increased slightly.

The following figure shows an example screenshot of the prediction system in action:

Metric	Value	
Training Loss (MSE)	0.0021 Validation Loss	0.0038
Average RMSE	7.42 pixels	
Prediction Rate	~20 Hz	

Figure 1: Live prediction of cursor trails in GUI (blue: actual, red: predicted)

The GUI successfully demonstrates the system's prediction and its visualization interface with real-time feedback.

V. APPLICATIONS

1) *Web Browsing:* Pre-loading elements or auto-highlighting links.
2) *Gaming:* Predictive targeting or control automation.
3) *Accessibility:* Reduced click effort for users with motor impairments.
4) *UI/UX Optimization:* Real-time response to predicted user intent

VI. CONCLUSION

The Predictive Cursor Behavior System demonstrates the feasibility of using deep learning to enhance human-computer interaction. Through LSTM-based prediction and interactive GUI visualization, the system offers a step toward anticipatory interfaces. With further refinement, it can be adopted in various applications ranging from accessibility aids to intelligent UIs and gaming enhancements.

VII. ACKNOWLEDGEMENT

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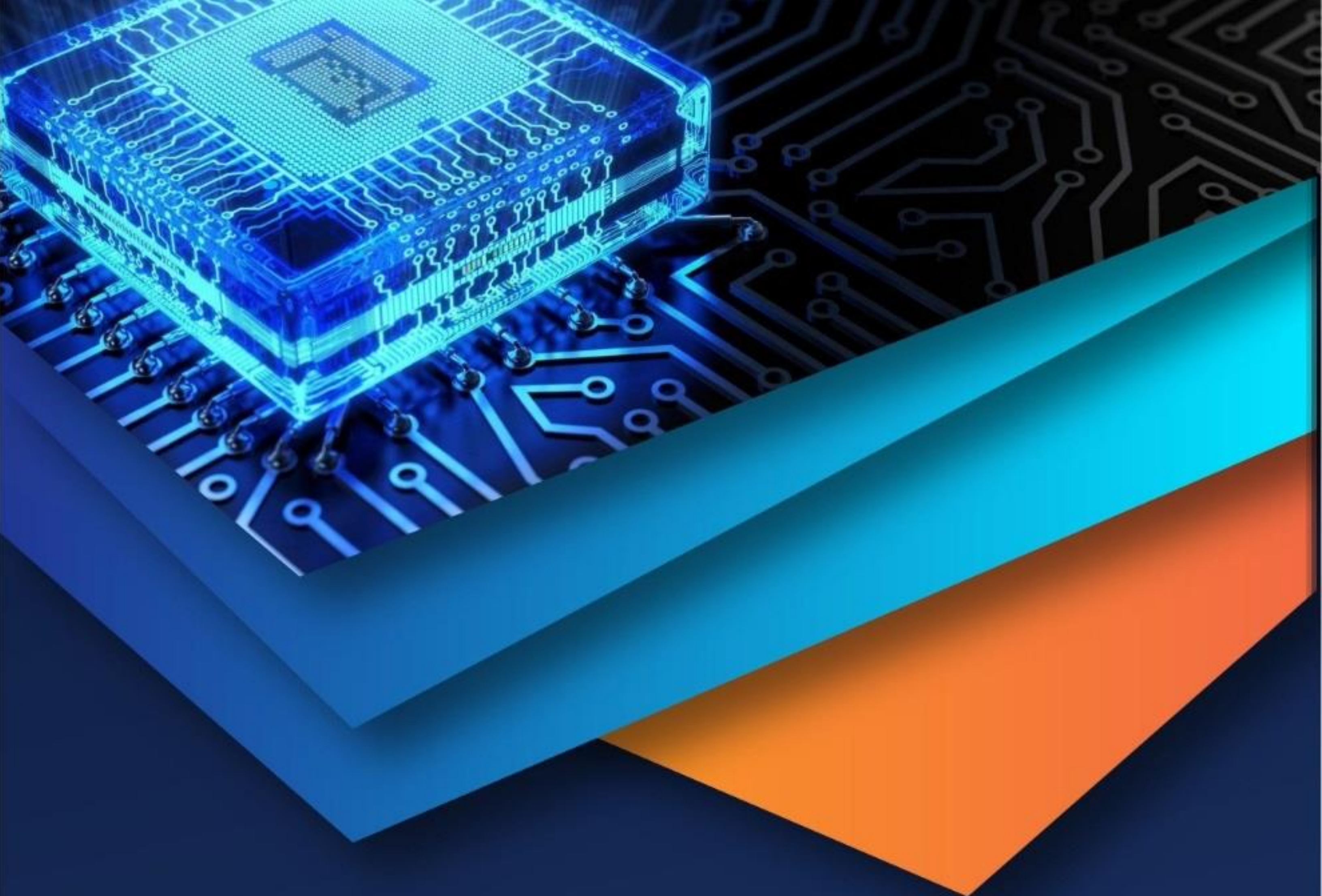

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