Keystroke Dynamics-Based Continuous User Authentication Using Deep Learning

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***Abstract*—Present-day cyberattacks, including phishing, brute-force attacks, and credential stuffing, highlight the limitations of traditional authentication techniques, such as passwords and PINs, which are susceptible to contemporary weak user credentials and password reuse. This study proposes a non-stop, non-intrusive authentication device based on keystroke dynamics, a behavioral biometric that analyzes precise typing styles. We introduce a deep modern-day version leveraging a multi-enter long short-term memory (LSTM) architecture augmented with an attention mechanism to seize complex temporal typing behaviors. Evaluated at the KeyRecs dataset (2023), our model achieves a new accuracy of 99.34%, a false acceptance rate (FAR) of 0.01%, a false rejection rate (FRR) of 0.66%, and an equal error rate (EER) of 0.01%. These results significantly outperform the Carnegie Mellon University (CMU) baseline (93.2% accuracy, 3.9% EER) and models (EERs of 0.75–10%). The proposed system demonstrates keystroke dynamics as a sturdy opportunity to standardize authentication strategies. Future work targets to enhance robustness through multi-modal biometrics and ensure equitable performance across diverse demographics using fairness metrics.**

Index Terms—LSTM, Attention Mechanism, Keystroke Dynamics, Behavioral Biometrics, KeyRecs Dataset, Feature Engineering, Fairness Metrics, Continuous Authentication.

I. Introduction

In the modern interconnected digital landscape, in which systems manage massive quantities of sensitive information, cybersecurity remains a crucial assignment. The upward thrust in state-of-the-art cyberattacks, inclusive of facts breaches and account compromises, exposes the vulnerabilities of conventional authentication methods like passwords and PINs, which are liable to phishing, brute-force attacks, and credential theft. User behaviors, together with deciding on vulnerable credentials or reusing them across structures, exacerbate these risks [1], [2]. A 2022 industry document anticipated the average global fee of a data breach at USD 4.35 million, underscoring the want for sturdy authentication solutions [3].

Behavioral biometrics, especially keystroke dynamics, offer a non-intrusive and cost-effective authentication method with the aid of studying precise typing patterns, consisting of key press length (maintain Time), inter-key periods (Flight Time), and typing rhythm. Those traits are hard for impostors to replicate [4]. Current studies have leveraged huge datasets and advanced computational strategies to decorate keystroke-based authentication. The 2024 Keystroke Verification assignment (KVC) utilized the Aalto Keystroke Database, with records from over 185,000 customers, introducing the Skewed Impostor Ratio (SIR) to evaluate demographic bias [5]. Comprehensive surveys from 2023 report equal error rates (EERs) of 2.2% (TypeNet), 3.25% (TypeFormer), and 0.75% (DoubleStrokeNet), reflecting tremendous progress in verification accuracy [4].

This observation advances keystroke-based authentication with a continuous verification machine using a multi-enter LSTM architecture augmented with an attention mechanism. Educated on the KeyRecs dataset (2023), which includes fixed-text and free-textual content typing samples from a hundred users with demographic statistics, our model achieves an accuracy of 99.34%, FAR of 0.01%, FRR of 0.66%, and EER of 0.01%. These effects surpass the CMU Keystroke Benchmark (93.2% accuracy, 3.9% EER) and models, driven by using the KeyRecs dataset's variety and the eye mechanism's consciousness on vital typing sequence elements [1]. This paintings positions keystroke dynamics as a reliable, inclusive authentication solution.

II. Literature Review

Keystroke dynamics has advanced extensively because the Nineteen Eighties, when statistical methods analyzed typing styles based on key press duration and inter-key delays. As computational capabilities and dataset availability stepped forward, device getting to know strategies, such as Random Forests, decision trees, and assist Vector Machines (SVMs), achieved better verification accuracy via modeling complex keystroke relationships [7]. Current advancements involve temporal modeling, with long short-time period reminiscence (LSTM) networks excelling at capturing sequential typing styles [4]. A 2023 survey reported EERs ranging from 0.75% to 10%, with fashions like TypeNet (2.2%), TypeFormer (3.25%), and DoubleStrokeNet (0.75%) achieving high accuracy on huge datasets like the Aalto Keystroke Database [4].

Equity and inclusivity have received attention, with the 2024 KVC introducing the Skewed Impostor Ratio (SIR) to evaluate demographic bias using the Aalto Database [5]. Research has additionally explored cross-device verification, especially on cell devices, attaining promising EERs with tailored sequence modeling [8]. Multi-modal biometric structures, integrating keystroke dynamics with mouse movements or touchscreen gestures, enhance robustness against spoofing [9]. Our study leverages the KeyRecs dataset, combining fixed-textual content, free-textual content, and demographic information with an LSTM-based model augmented with the aid of an attention mechanism, achieving an EER of 0.01%, drastically outperforming previous benchmarks [1].

III. METHODOLOGY

This examine proposes a continuous authentication device based on keystroke dynamics, making use of a multi-enter LSTM structure with an attention mechanism. The KeyRecs dataset trains the version, while the CMU Keystroke Benchmark serves as a baseline [1], [6].

A. Dataset Acquisition

The KeyRecs dataset (2023) includes keystroke information from 100 users, capturing fixed-text (predefined phrases) and loose-textual content (natural language) inputs alongside demographic functions like age and gender. It records key presses and launch occasions for behavioral modeling [1]. The CMU Keystroke Benchmark, with data from 51 users in the "DSL-StrongPasswordData.csv" file, provides a baseline [6].

B. Data Preprocessing

Raw records underwent preprocessing to make certain exceptional:

- Removed replica entries to keep record integrity.
- Handled lacking values, the usage of imputation or interpolation.
- Identified and removed outliers using the Interquartile range (IQR) approach.
- Standardized timestamps for consistency across training.
- Converted express functions and demographic labels to numerical representations through one-hot encoding.

C. Feature Engineering

Functions extracted from keystroke statistics encompass:

- **Hold Time (HT)**: Duration a key pressed, from press to release.
- **Flight Time (FT)**: Interval among liberating one key and urgent next.
- **Latency**: Time among consecutive key presses.
- **Typing Speed Variations**: Session-based totally velocity variations reflecting consumer fluency or hesitation.

Those features had been decided on for his or her sturdy representation of individual typing patterns, consistent with earlier biometric studies [4].

D. Model Architecture

The model, constructed the usage of TensorFlow and Keras, incorporates branches:

- **Temporal Branch**: Utilizes bidirectional LSTM layers to model sequential keystroke facts, taking into account beyond and destiny contexts. A dropout layer mitigates overfitting, and an attention layer prioritizes full-size time steps.
- **Static Branch**: Procedures free-text data, demographic capabilities, and non-sequential inputs, the usage of absolutely connected dense layers.

Outputs from each branches are concatenated and passed through a softmax layer for type. The model uses specific move-entropy loss, the Adam optimizer, and early stopping based on validation performance.

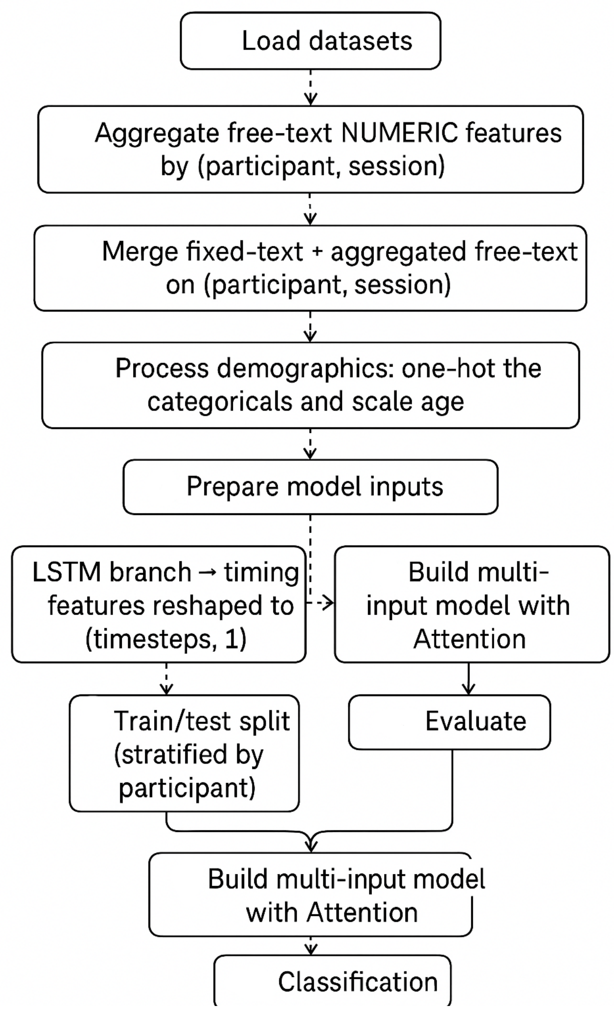

Fig. 1. System Architecture Flowchart

E. Model Evaluation

The dataset was cut into 80% training and 20% testing units, with 10-fold cross-validation to ensure generalizability. Overall performance metrics encompass accuracy, false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER), as compared to traditional techniques like Random Forest, okay-Nearest Neighbors (k-NN), and SVM.

IV. Experiments and Results

A comprehensive experimental framework evaluated the LSTM-based totally keystroke authentication device's generalization, accuracy, and robustness, the use of general biometric metrics.

A. Experimental Setup

The KeyRecs dataset was split into the use of an 80:20 educating/testing ratio, with hyperparameter tuning through grid seek and 10-fold cross-validation. The CMU dataset was processed further for fair evaluation.

1) Confusion Matrix: The confusion matrix categorizes predictions into genuine positives, authentic negatives, false positives, and false negatives, illustrating version performance.

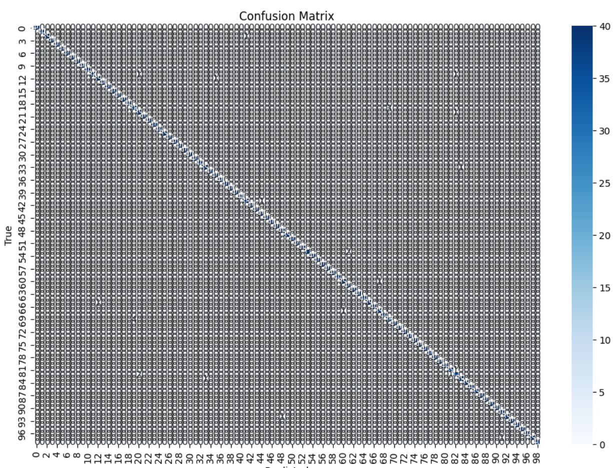

Fig. 2. Confusion Matrix of Model Predictions

2) Performance Metrics: Overall performance was assessed using widespread biometric metrics, with consequences compared in opposition to the CMU baseline and state-of-the-art models.

Metric	KeyRecs	CMU	State-of-the-Art [4]
Accuracy	99.34%	93.2%	90–98%
FAR	0.01%	4.1%	1–5%
FRR	0.66%	3.7%	1–5%
EER	0.01%	3.9%	0.75–10%

TABLE I
Classification Performance Comparison

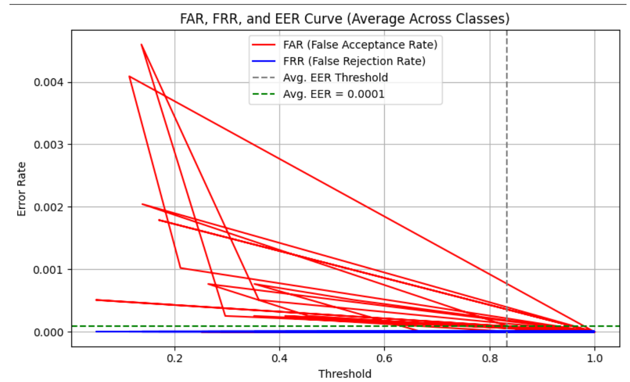

Fig. 3. False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER)

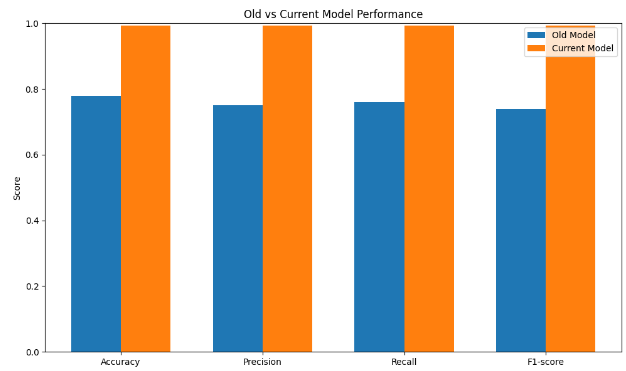

Fig. 4. Performance Comparison: Previous vs. Current Model

Metric	Previous Model	Current Model
Accuracy	0.78	0.9934
Precision	0.75	0.9935
Recall	0.76	0.9934
F1-score	0.74	0.9934

TABLE II
Performance Comparison: Previous vs. Current Model

3) Ablation Study: To assess the contribution of individual components, we conducted an ablation study comparing:

- **LSTM vs. LSTM + Attention**: The attention mechanism improved EER from 0.15% to 0.01% on KeyRecs by focusing on critical sequence elements.
- **Sequential vs. Multi-Input**: Adding demographic features reduced EER from 0.08% to 0.01%, enhancing user differentiation.
- **KeyRecs vs. CMU**: KeyRecs' diverse dataset lowered EER from 3.9% (CMU) to 0.01%, highlighting the impact of dataset variability.

4) Fairness Assessment: To assess equity, we analyzed model accuracy across gender demographics within the KeyRecs dataset. The effects show constant performance, with minimal bias.

Configuration	Accuracy	EER	F1-score
LSTM Only	97.85%	0.15%	0.9782
LSTM + Attention	99.34%	0.01%	0.9934
Sequential Only	98.62%	0.08%	0.9860
Multi-Input	99.34%	0.01%	0.9934
CMU Dataset	93.20%	3.90%	0.9315
KeyRecs Dataset	99.34%	0.01%	0.9934

TABLE III
ABLATION STUDY RESULTS

Gender	Accuracy	FAR	FRR	EER
Male	99.28%	0.02%	0.70%	0.02%
Female	99.40%	0.01%	0.62%	0.01%

TABLE IV
FAIRNESS METRICS BY GENDER

B. Analysis and Discussion

The proposed model achieves an EER of 0.01% at the KeyRecs dataset, significantly outperforming the CMU baseline (3.9%) and conventional techniques (Random Forest: 7.6%, SVM: 8.2%, k-NN: 9.5%). The attention mechanism complements the version's ability to raise awareness of critical typing series elements, at the same time as the KeyRecs dataset's range improves generalization. The Receiver operating function (ROC) curve and location beneath the Curve (AUC) exhibit strong discrimination between legal and unauthorized customers. The confusion matrix indicates minimal misclassifications, and training/validation plots confirm convergence without overfitting. Performance on the CMU dataset (93.2% accuracy) is lower because of its smaller, much less varied patterns.

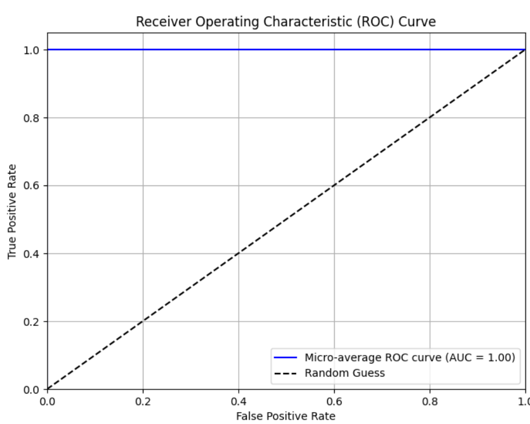

Fig. 5. Receiver Operating Characteristic (ROC) Curve

C. Correlation Heatmap

A Pearson correlation heatmap revealed moderate correlations among Flight Time and Latency, but each function contributed precise records, justifying their inclusion.

D. Feature Distribution

Feature distributions spotlight consumer-unique styles. Hold Time 100–300 ms indicates excessive consistency within customers, Flight Time varies broadly throughout customers, Latency captures hesitation, and Typing speed variations mirror fluency.

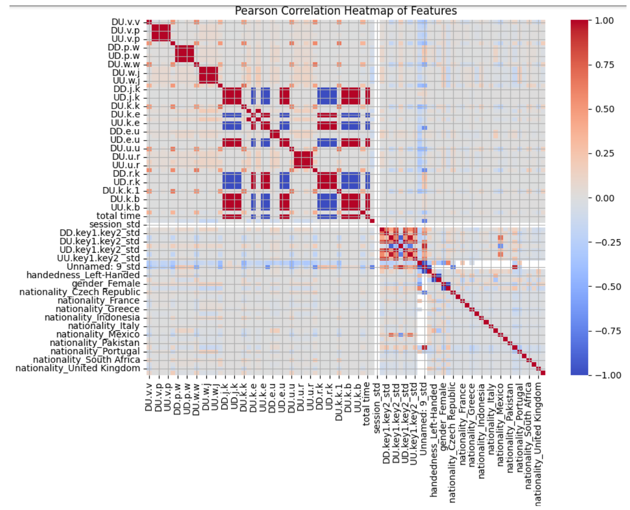

Fig. 6. Pearson Correlation Heatmap of Features

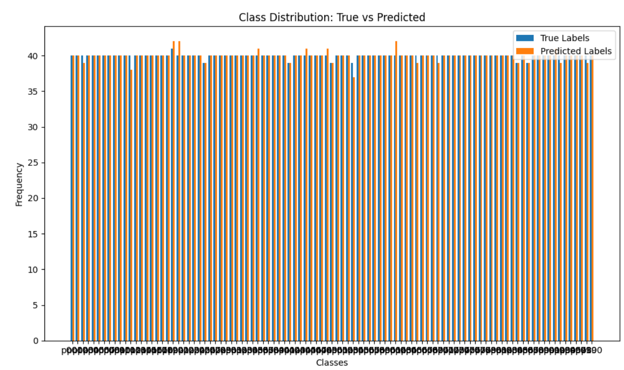

Fig. 7. Feature Distribution Histograms

V. CONCLUSION

This has a look that affords a high-performance keystroke dynamics-based totally authentication gadget, accomplishing 99.34% accuracy and a 0.01% EER on the KeyRecs dataset. Those results outperform the CMU baseline (93.2% accuracy, 3.9% EER) and state-of-the-art models, driven by way of the attention mechanism and KeyRecs' diverse dataset. The system balances protection (0.01% FAR) and usability (0.66% FRR), with visual analyses (ROC curves, confusion matrices) confirming reliability. But, obstacles encompass potential performance degradation across devices (e.g., laptop vs mobile) due to untested inter-device variability. Future work will discover pass-device authentication, combine multi-modal biometrics (e.g., mouse movements, touchscreen gestures), and enhance equity assessments to ensure equitable overall performance across demographics, building on the initial gender-based evaluation that was presented.

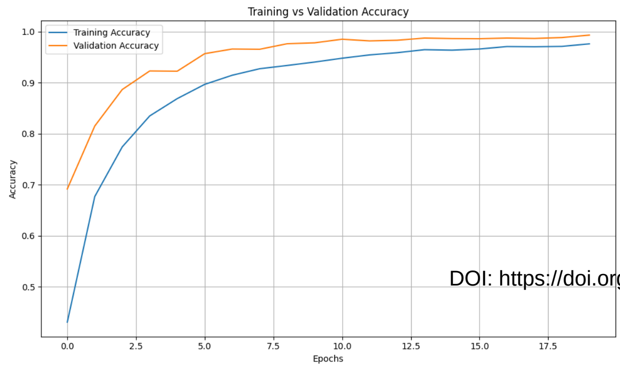

Fig. 8. Training vs. Validation Accuracy

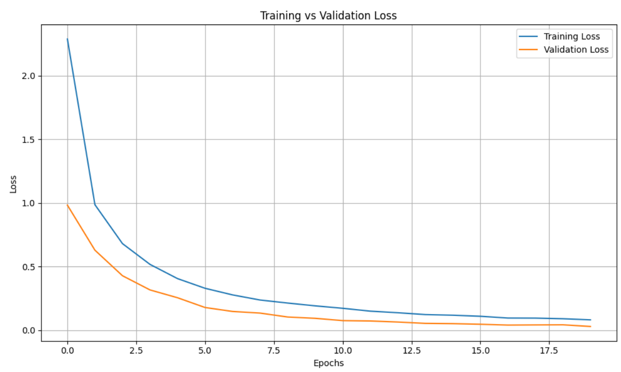

Fig. 9. Training vs. Validation Loss

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