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PROJECT REPORT
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“TRI FACTOR AUTH”

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Dec 2024



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DECLARATION

I hereby declare that the thesis entitled “**Tri Factor Auth**” is a research work done by me and no part of the thesis has been presented earlier and will be presented for any degree, diploma or similar title at any other institute/university.

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ABSTRACT

The current minor project introduces a keystroke-based CAPTCHA system targeted at distinguishing between human users and bots by considering the dynamics of keystrokes. The challenge in the project is that bots, due to their sophistication in use of machine learning techniques, have managed to mimic human typing patterns, hence it's challenging to distinguish a bot from a human user. This project counters this through generating synthetic bot data with characteristics of human-like typing behaviour and comparing it against real human typing data in the training of a robust detection model.

The CAPTCHA system uses machine learning classifiers like “Support Vector Machines, Random Forests, Gaussian Naive Bayes, and Long Short-Term Memory networks” to distinguish between the typing patterns of humans and bots. Results show that the system is able to identify bots, including those trained to mimic human typing dynamics. This new approach makes the CAPTCHA systems more reliable and secure by using both synthetic and real data in order to make the mechanisms for bot detection more robust.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AAA	Authentication, Authorization, and Accounting
CIA	Confidentiality, Integrity & Availability
CAPTCHA	Completely Automated Public Turing test to tell Computers and Humans Apart

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1. INTRODUCTION

1.1 Purpose

The increasing trend of Artificial Intelligence (AI) in cyber threats has become a critical issue for society. With the increase in internet usage across the globe, bots have been increasingly used to access digital platforms, which have caused severe economic and operational challenges. The detection of these bots is a complex issue. Over the last decade, generative models have advanced to the point where they can create highly realistic images, videos, audio, and text, which enables bots to behave like humans. For instance, the modern language models have made it nearly impossible to differentiate between bot and human interactions. In this context, biometric technologies seem to be a promising avenue for differentiation between genuine and synthetic behaviours. Biometric authentication is based on the unique attributes of physical characteristics or behavioural patterns and is used for the identification of an individual, to verify users, to classify into groups, and to differentiate between humans and bot activities. This work concentrates on detecting bots using the synthesis and detection of synthetic keystroke patterns. Keystroke biometrics is ideal for this use since it is so universally prevalent in digital interaction involving keyboards and touch screens.

Bot detection systems try to distinguish legitimate user interactions from malicious bot activities. The traditional approaches used include cognitive challenges that involve distorted text interpretation or specific object selection within images. However, these traditional approaches have been made ineffective by progress in computer vision and deep learning. As a result, newer CAPTCHAs exploit passive behavioural data, which includes keystroke dynamics and mouse movements, to allow for unobtrusive differences between bots and humans.

1.2 AIM/OBJECTIVE

This project proposes Five methodologies for synthesising keystroke dynamics data with direct applications in bot detection. Key contributions include:

Development of Five synthetic data generation methods: universal statistical modelling, user-specific modelling, generative neural network-based approach, LSTM memory, HMM, Reinforcement learning.

A bot detection framework trained on both human and synthetic keystroke data is introduced.

A detailed analysis of the proposed approaches, are discussed by considering how data volume, synthetic data quality, and text dependencies influence classification accuracy.

1.3 SCOPE

This project is a robust and scalable bot detection framework using synthetic keystroke dynamics data. The objective of the framework is to differentiate between human and bot behaviour through typing patterns, making use of advanced data generation techniques in order to improve the detection accuracy and robustness of the system. It is going to be an asset in cybersecurity because systems are going to be able to detect automated bots on a wide variety of platforms such as login forms, online surveys, e-commerce websites, and much more.

A critical component of this framework is the synthetic data generation methodology, which addresses the challenge of acquiring large, labeled datasets for training bot detection models. Traditional methods of data collection for keystroke dynamics often face limitations due to privacy concerns, high costs, and insufficient labeled bot data. To overcome this, the project proposes using reinforcement learning and key-sequence contextual synthesis to generate realistic and diverse keystroke dynamics data. By using these techniques, the project will generate a rich dataset that resembles human typing patterns but is diverse enough to simulate a wide range of typing behaviours, including different demographics, typing speeds, and error types.

Further to this approach of Hybrid Statistical and Generative Models, the synthetic data would then further be quality-impacted to cover all universal human behaviours while catering for specific individual user-specific patterns. When training models for the detection task, the system should have generalisation better capabilities because new and complex bots would imitate humans and present specific telltale signs if subjected to very sophisticated algorithms for their detection.

2. Literature Survey

2.1 Current/Existing Systems

2.1.1 Study of Current System

Bot detection systems have extensively protected digital platforms from automated attacks, fraud, and other malicious activities. These are differentiated among human users and bots in different behavioural and interaction patterns. Below is an overview of existing systems used for bot detection. The strengths and limitations have been highlighted.

A. CAPTCHA Systems

Overview: CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart) are probably the most prevalent bot detection technique. This technique usually forces users to perform a task that is straightforward for humans but problematic for automation systems, such as recognising jumbled characters in an image or solving puzzles [1].

Limitations:

Bots have evolved to become very sophisticated. They are using OCR or deep learning to solve CAPTCHA challenges [2].

User experience: CAPTCHAs are annoying and frustrating to deal with, especially on mobile [3].

Susceptible to "Captcha farms" where humans solve CAPTCHAs for bots at scale [4].

B. Keystroke Dynamics for Authentication

Overview: Keystroke dynamics, a form of behavioural biometrics, use patterns in typing behaviour such as typing speed, rhythm, and pauses between key presses to identify users. It's applied in security systems to authenticate users based on their unique typing signatures [5].

Limitations:

The user's physical condition, device, or typing environment can influence the accuracy of this method, such as ergonomic issues or keyboard type [6].

This can be spoofed by sophisticated bots programmed to emulate the typing of humans [7].

It needs large amounts of labeled data to train good models [8].

C. Traffic Analysis and Heuristics

Overview: This method involves analysing web traffic patterns, such as request frequency, IP address analysis, session behaviours, and mouse movement patterns, to detect anomalous or bot-like activities [9].

Limitations:

Bots can camouflage their activities by mimicking human-like traffic patterns. For example, slowing down the intervals of requests or using a

proxy to hide the IP address [10].

Lack of discrimination between types of legitimate users and bots, resulting in false positives [11].

D. Machine Learning-Based Bot Detection

Overview: Advanced bot detection engines employ ML algorithms like “Random Forests”, “Support Vector Machines SVM”, or “Neural Networks”, in order to classify user behaviour and identify the bots through different features, from time spent on a page through mouse movements to typing patterns [12].

Limitations:

Includes the need for large labeled databases of both bot and human data for proper training to occur [13].

It is vulnerable to adversarial attacks where bots are trained to mimic human behaviour, making it difficult for the model to distinguish between the two [14].

False positives and negatives can occur, especially if the training data is not sufficiently diverse [15].

E. Browser Fingerprinting

Overview: Browser fingerprinting is a method that collects a very wide range of data about the user's browser and device configuration, such as screen resolution, plugins, fonts, and many other properties of the browser, to create a unique "fingerprint" for each user. Bots usually are unable to reproduce complex fingerprint characteristics [16].

Limitations:

Fingerprinting is privacy-invasive and raises concerns about user tracking and data privacy [17].

Bots can use headless browsers or manipulate their environment to change their fingerprint [18].

Difficult to distinguish between legitimate users with similar configurations [19].

F. Hybrid Approaches

Overview: Many modern bot detection systems combine multiple techniques, such as CAPTCHA, traffic analysis, machine learning, and keystroke dynamics, to improve accuracy and robustness [20].

Limitations:

Complexity in putting together various techniques in a unified and efficient manner [21].

Computational cost has increased significantly in systems where machine learning models or real-time data analysis is applied [22].

Inconvenience to users, because multiple checks may be involved in the system [23].

G. AI-Driven Bot Detection

Overview: Advances in “Artificial intelligence” (AI) and deep learning enable the development of more sophisticated bot detection systems. These systems can learn from vast amounts of data and adapt to evolving bot behaviours. They use techniques like “deep neural networks” (DNN) or “recurrent neural networks” (RNN) to model more complex relationships in data and detect subtle bot activities [24].

Limitation:

Highly requires big data and computational powers to train models [25].

Adversarial attacks whereby bots are trained to evade detection through the AI systems [26].

It may be resource-intensive and may not be feasible for small websites or services [27].

2.1.2 Problem & Weakness of Current System

Current systems for bot detection are very effective but face several challenges, such as:

Sophistication of Bots: Bots are becoming increasingly sophisticated, able to mimic human-like behaviour in ways that bypass traditional detection methods like CAPTCHAs and heuristics [28].

Data Privacy and Scalability: The need for large labeled datasets for training machine learning models often conflicts with privacy concerns. Furthermore, systems must be scalable to handle vast amounts of web traffic [29].

False Positives and False Negatives: Current models may wrongly classify legitimate users as bots (“false positives”) or fail to identify advanced bots (“false negatives”) [30].

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2.2 Requirements of New System

2.2.1 Technical Feasibility

Keystroke dynamics-based approaches are technically feasible and have been demonstrated in both user recognition and bot detection contexts. The use of Deep Neural Networks (DNNs) for free-text keystroke recognition has resulted in significant improvements in performance, reducing Equal Error Rates (EER) to under 5% in some cases [31]. The synthesis of keystroke data using Generative Neural Networks (GNNs) for bot detection, as well as the development of synthetic keystroke datasets, such as the Dhakal Dataset, presents a technically sound basis for further research and practical applications. In addition, recent advances in statistical synthesis techniques such as Markov Chains and Support Vector Machines (SVMs) show that realistic keystroke data can be generated, further justifying the possibility of synthesising data for bot detection models [32].

Key technical challenges include:

Modelling keystroke dynamics of human users and bots.

Generalisation of models to different typing styles and keyboard layouts.

Developing models that can differentiate between real users and sophisticated bot behaviour with high accuracy.

However, this is technically possible using the recent advances in machine learning, especially deep learning and Long Short-Term Memory, given the availability of large-scale datasets [33].

2.2.2 Operational Feasibility

In terms of operational feasibilities, with sufficient resources, implementation of keystroke dynamics-based bot detection systems is feasible. The existence of large datasets such as the Dhakal Dataset (with more than 168,000 subjects and 136 million keystrokes) allows for more than sufficient data to create robust models [34]. In addition, deep learning frameworks in use (for example, TensorFlow, PyTorch) make model training and deployment highly scalable [35].

However, operational challenges could be in the following areas:

Data Collection: How the keystroke data is collected such that user privacy is maintained and regulatory standards are adhered to (e.g., GDPR, CCPA) [36].

Real-Time Detection: The real-time environment in which bot detection systems must process keystroke data with minimal latency [37].

User Variation: The handling of different patterns among individuals, which will vary between users and thus can be considered to impact both the human recognition model and the bot detection model [38].

While these issues are definitely controllable through proper design, the

operational feasibility is indeed very high with proper infrastructure and resources in place.

2.3 Tools / Technology Required

The following tools and technologies would be necessary for successful development and deployment of keystroke dynamics-based bot detection systems:

Data Collection Tools:

Keystroke data collection software to capture the typing patterns.

Integrate with various input devices and operating systems to ensure cross-platform support [39].

Machine Learning Libraries:

Deep Learning Frameworks: For training neural networks and generative models, TensorFlow, PyTorch, and Keras [40].

Classical Machine Learning Libraries: Scikit-learn for more traditional machine learning algorithms, such as SVMs and Euclidean distance classifiers [41].

Generative Neural Networks (GNNs): Custom generative neural networks that produce realistic keystroke data, therefore enhancing the accuracy of bot detection [42].

Data Processing and Analysis:

Keystroke processing tools (e.g., Pandas, NumPy) to extract features like Hold Latency, Press Latency, Release Latency, Inter-Key Latency, and Key Code.

Statistical tools for feature analysis and model evaluation [43].

Database Management:

Relational or NoSQL databases (e.g. MySQL, MongoDB) to keep record of keystroke data as well as synthetic samples [44].

Cloud infrastructure (e.g. AWS, Google Cloud) for scalable storage and computation [45].

Security and Privacy Tools:

Use cryptographic methods to handle sensitive data by users in a proper secure manner. Anonymise user identity in datasets. Real-time keystroke analysis and bot detection systems, possibly built upon server less computing or micro-services architecture [46].

Conclusion: Keystroke dynamics data synthesis for bot detection is technically and operationally possible using the right tools and technologies to support the building of a robust system.

3.Design: Analysis, Design Methodology and Implementation Strategy

3.1 Function of System

3.1.1 Use Case Diagram

Use Case	Actor(s)	Class	Objects
Synthetic Keystroke Generation	System Administrator	SyntheticGenerator	<ul style="list-style-type: none">- Universal Model- User-dependent Model- GNN Model
Keystroke Feature Extraction	User, System	KeystrokeFeatureExtractor	<ul style="list-style-type: none">- Hold Latency- Press Latency- Inter-Key Latency- Release Latency
Bot Detection	User, Bot, System Administrator	BotDetectionSystem	<ul style="list-style-type: none">- SVM Classifier- LSTM Classifier- Random Forest- Gaussian Naive Bayes
Performance Analysis	System Administrator	PerformanceAnalyzer	<ul style="list-style-type: none">- Real Data Samples- Synthetic Data Samples- Evaluation Metrics

Fig1

3.1.2 Activity Diagram

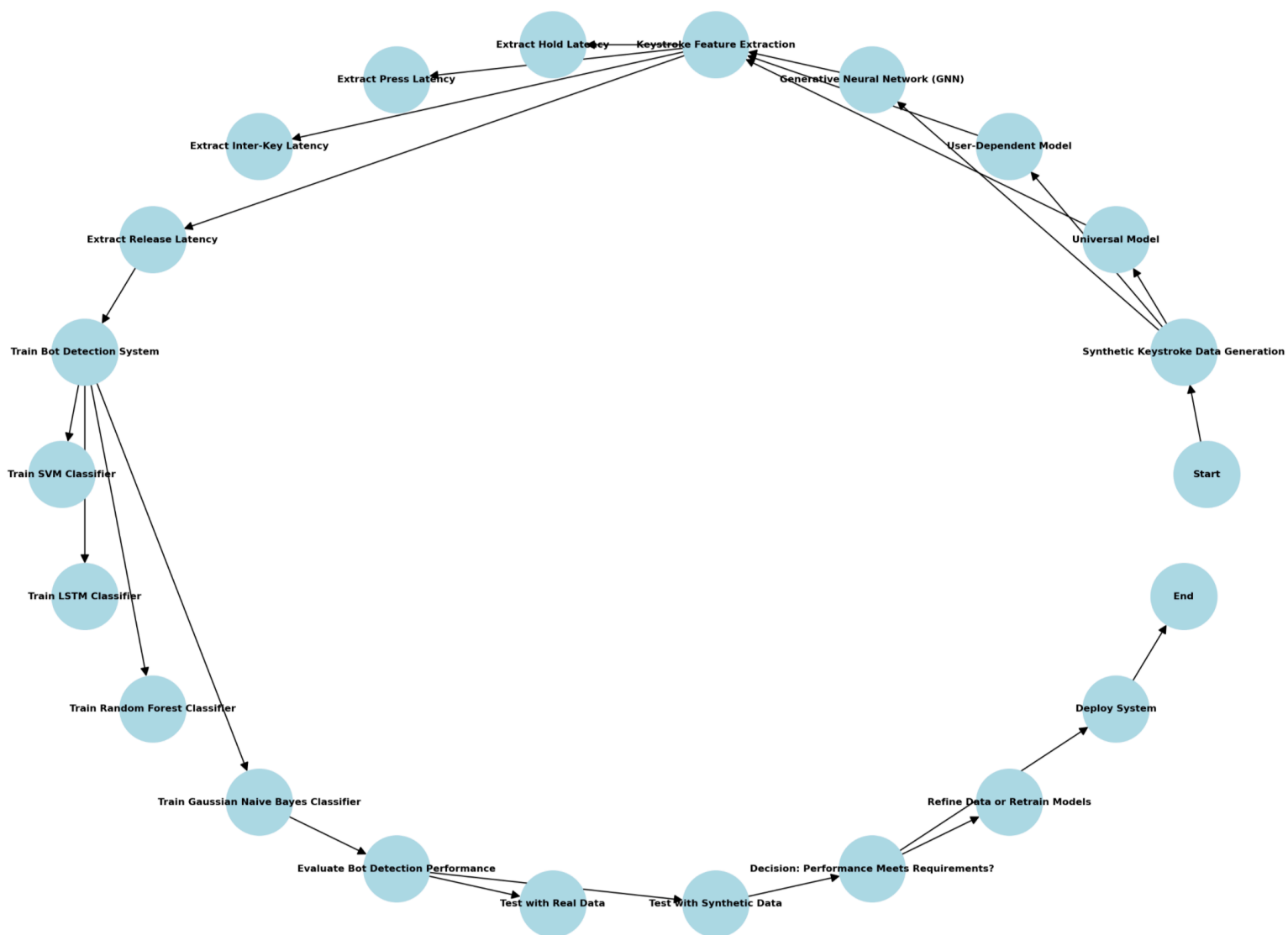


Fig 2

3.1.3 Sequence Diagram



Fig 3

3.2 DATA MODELLING

3.2.1 Entity-Relationship Diagram

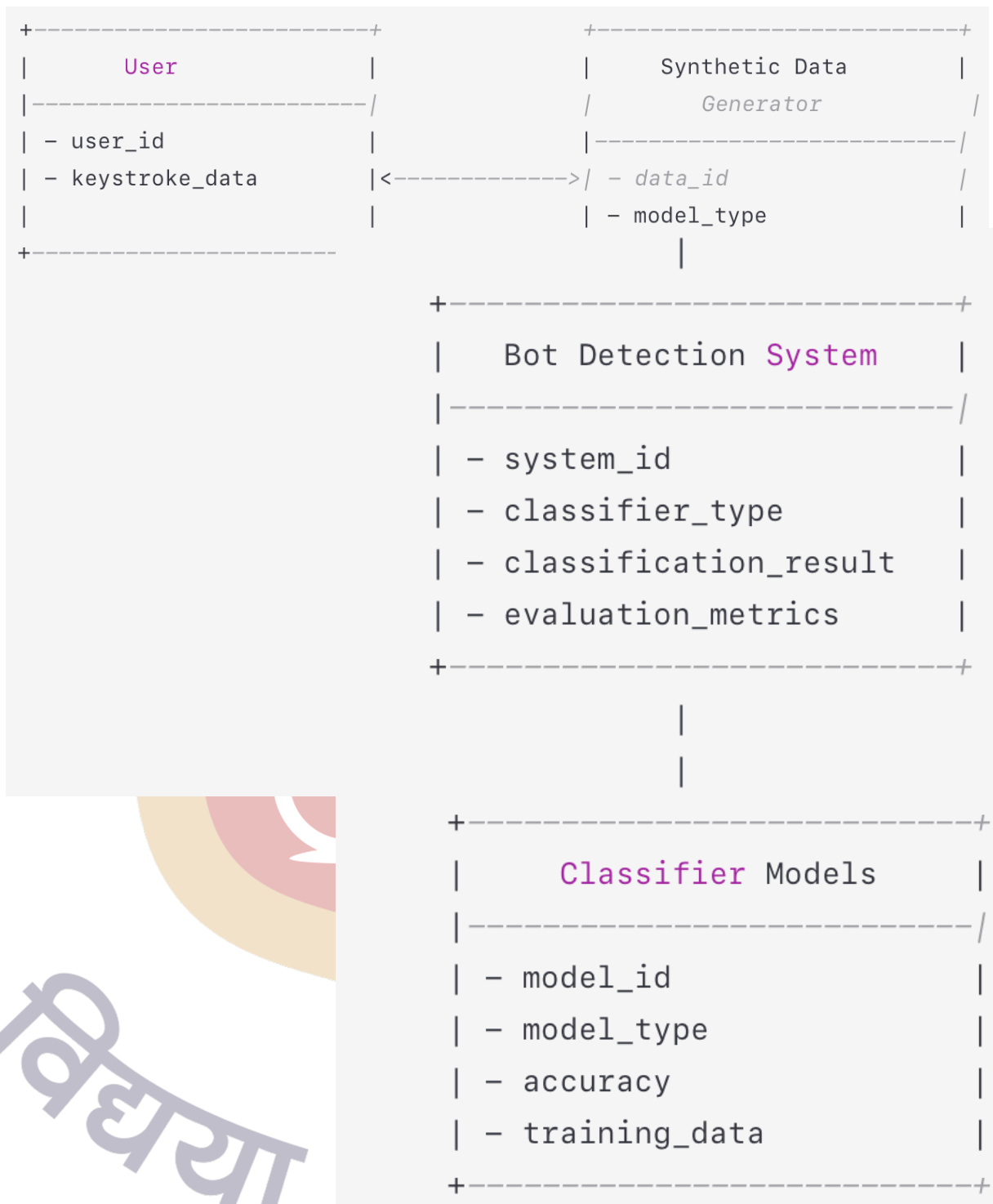


Fig 4

3.2.2 Class Diagram



Fig 5

3.3 Functional & Behavioural Modelling

3.3.1 Data Flow Diagram

Level 0 context diagram

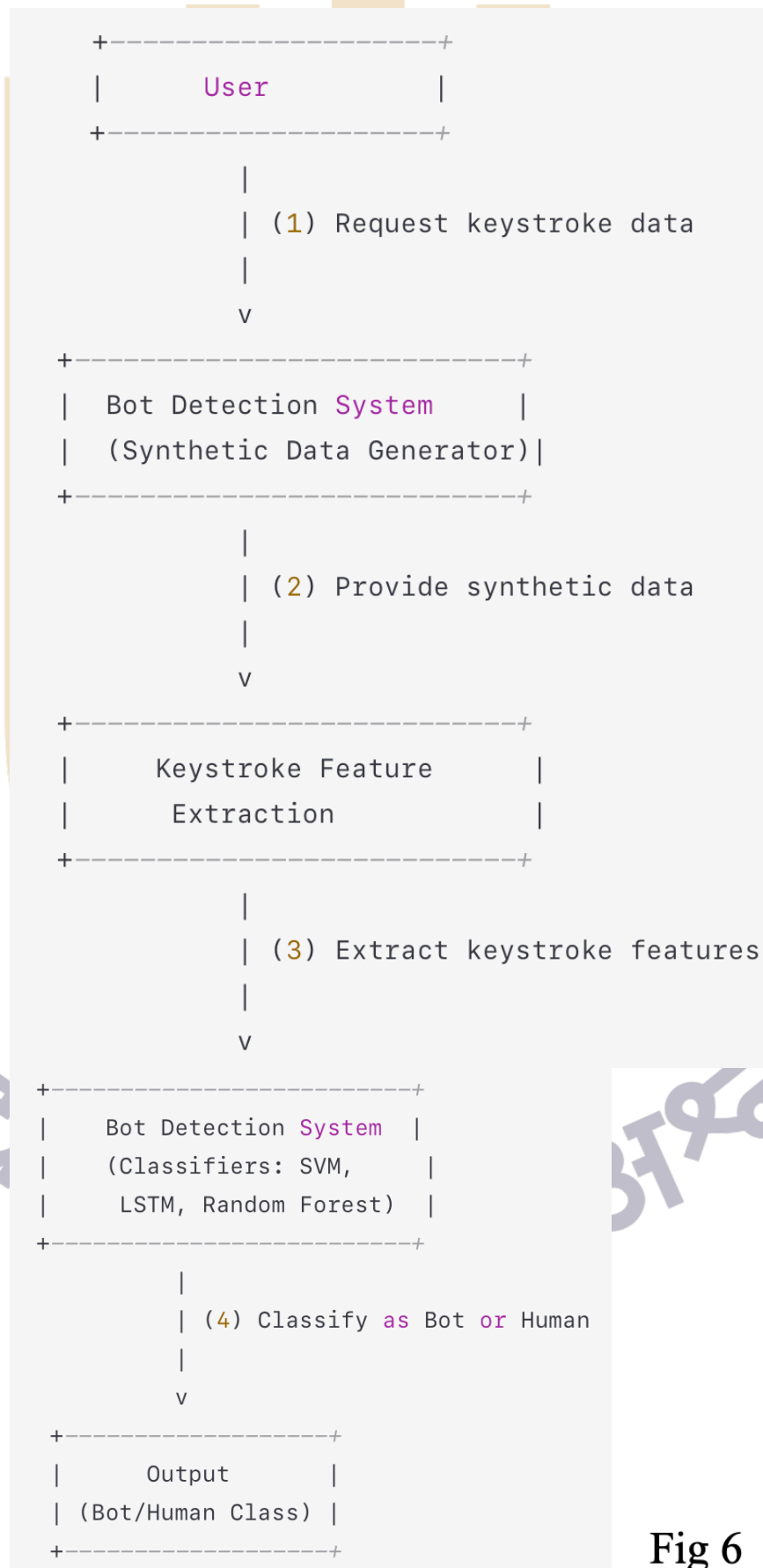


Fig 6

Level 1 Detailed DFD

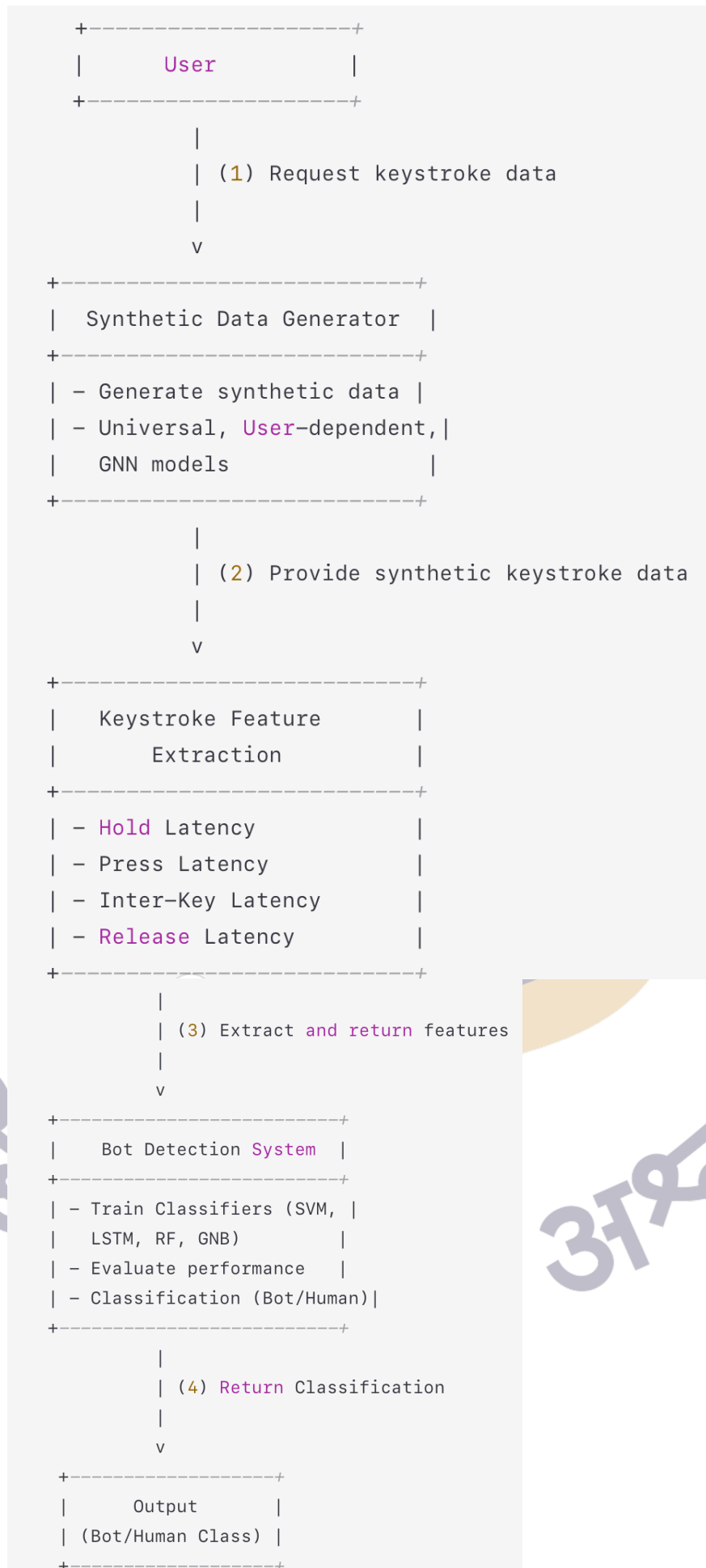


Fig 7

3.3.2 Data Dictionary

```

+-----+
| User |
+-----+
| - user_id |
| - keystroke_data |
+-----+
| Description: Unique identifier and |
| keystroke data of the user. |
|
|
+-----+

|
| (1) Request keystroke data
v
+-----+
| Keystroke Feature Extractor |
+-----+
| - feature_id |
| - hold_latency |
| - press_latency |
| - inter_key_latency |
| - release_latency |
+-----+
| Description: Extracts key |
| features (latency times) |
| from the keystroke data. |
+-----+

|
|
v
+-----+
| Classifier Models |
+-----+
| - model_id |
| - model_type |
| - accuracy |
| - training_data |
+-----+
| Description: Stores machine |
| learning models used in bot |
| detection. |
+-----+

+-----+
| Synthetic Keystroke |
+-----+
| Data |
+-----+
| - data_id |
| - model_type |
+-----+
| - generated_data |
| Description: Data generated |
| by different models for |
| bot detection. |
+-----+

|
|
v
+-----+
| Bot Detection System |
+-----+
| - system_id |
| - classifier_type |
| - classification_result |
| - evaluation_metrics |
+-----+
| Description: Processes data |
| for classification using |
| classifiers (SVM, LSTM, etc.) |
+-----+

| ,
| (2) Provide features
v
+-----+
| Output |
+-----+
| - classification_result |
| - performance_metrics |
| Description: The result |
| of bot classification (Bot/ |
| Human). |
+-----+

```

Fig 8

4. Implementation

4.1 Implementation Environment

4.1.1 Model Used in Developing

4.1.1.1 Stats Gen Model: Hidden Markov Model (HMM)

For the statistical approach, we make use of the Hidden Markov Model (HMM), which is a probabilistic model that is particularly effective in modelling temporal sequences. HMMs are well suited for modelling systems where the state at any given time depends on the previous state, which is exactly the case in keystroke dynamics where key press timings depend on previous key presses.

HMMs model keystroke biometric features as a sequence of hidden states. Each state corresponds to a different typing behaviour. The key press and release events are treated as a sequence of observations, and the model learns how to transition between hidden states based on the observed features.

The model is formulated as follows:

- **States:** The system is assumed to be in one of several hidden states and each hidden state is assumed to represent a different typing pattern. The hidden states are not observed directly but the observations (e.g., features of keystroke) will be generated based on these states.
- **Observations:** At every time step, the model produces an observed feature, for example, Hold Latency, Press Latency, etc. This observed feature depends on the current state. The model assumes the probability of seeing a feature x at time t , given a hidden state q_t , to be as follows: $P(x_t|q_t)$.
- **Transition Probabilities** Transition probabilities that allow for the moving of probabilities of changing from one hidden state to another: these can be denoted by $P(q_t|q_{t-1})$, for example, it could represent the probability of changing from state q_{t-1} to q_t .
- **Emission Probabilities:** The probability of emitting the observed keystroke feature x_t conditioned on the current hidden state q_t is represented by the formula as $P(x_t|q_t)$.
- **Initial State Probabilities:** This model also incorporates the initial state probabilities that give the chances for beginning in any given hidden state.

The Hidden Markov Model uses learned parameters for generating synthetic keystroke dynamics in order to create a sequence of keystroke events. A three-step approach is given for synthetic keystroke generation:

- **Generate Key Sequence:** A string of K keys representing the text typed is obtained: $k = [k_0, k_1, \dots, k_K]$
- **Feature synthesis** The corresponding keystroke biometric features f_i are synthesised from samples of the emission probability of the HMM learned. This random sampling again injects human-like variation between the synthetic samples.
- **Timestamp Generation:** A set of timestamps $t' = [t'_0, t'_1, \dots, t'_{2K}]$ is created by simulating key press and release events. The timestamps are computed as a function of the features f_1 (“Hold Latency”) and f_4 (“Inter-Key Latency”), which can be represented as follows:

$$\begin{aligned} t'_0 &= 0, & t'_1 &= t'_0 + f_1[1] & \text{(for key 1)} & \dots 1 \\ t'_2 &= t'_1 + f_4[1], & t'_3 &= t'_2 + f_1[2] & \text{(for key 2)} \end{aligned}$$

The Hidden Markov Model allows the creation of keystroke data that embodies both temporal dependencies and human-like variability in typing behaviour.

4.1.1.1.1 Stats Approach 1: “Universal Model” (HMM)

The Universal Model in the context of “Hidden Markov Model” is built on the estimation of one set of HMM parameters that would represent the typing behaviour of all subjects within the “Dhakar Dataset”. Such a model represents general human typing behaviour, based on one set of hidden states and transition/emission probabilities. This assumption is under the fact that all users generally have similar typing patterns that the model could approximate a group of human typing features.

In this method, the HMM is trained on all keystroke data in the dataset, and the model learns the state transition and emission probabilities that best explain the collective behaviour. This Universal Model requires only a single set of HMM parameters to generate synthetic keystroke data.

However, the Universal Model has limitations:

- This does not capture user-specific behaviours or correlations between keystroke features specific to different users.
- It also cannot model the dependency between keystrokes and specific keys. For example, typing patterns change based on the key pressed and the keys adjacent to it that is not present in the Universal Model.

The HMM-based Universal Model first parameterises real human keystrokes into time features, and then the HMM learns the transition and emission probabilities from the dataset. Finally, the model generates new synthetic keystroke features f' and timestamps t' by sampling from the learned HMM parameters. This approach is simple and generalisable across users but may result in unrealistic samples when fine-grained, user-specific typing behaviours are needed.

4.1.1.1.2 Stats Approach 2: “User-dependent Model” (HMM)

The basic principle behind keystroke biometric recognition systems is that typing patterns are unique to each individual user. The User-dependent generation method focuses on incorporating intra-user characteristics into the synthesis process. This approach models user-specific typing behaviours, which can vary significantly between individuals. However, the problem is that the data available for each user is usually limited, and thus, the User-dependent Model may not always be as accurate as the Universal Model when there is limited data for a particular user.

In the user-dependent HMM approach, the objective is to model the keystroke feature of each individual user. To this end, it captures the specific typing behaviour while using an HMM framework for modelling the intra-user variability in keystrokes. However, even when this approach captures intruder variability, it remains hampered in modelling key dependent features since it does not take an explicit consideration of how the choice of individual keys affects typing behaviour.

The process for applying the User-dependent HMM approach is as follows:

- **Data Partitioning:** Keystroke samples from the Dhakal Dataset are partitioned by user, separating the data for each individual subject.
- **Keystroke Parameterisation:** For each user u , the corresponding keystroke timestamps t_u are parameterised to obtain a sequence of four time-based features $f_{u,i}$ (such as Hold Latency, Press Latency, etc.).
- **Feature Modelling:** Each time feature of all the subjects is modelled independently with probability distributions by using the Hidden Markov Model (HMM). For every user u , the HMM is applied for learning the transition and emission probabilities of keystroke features $f_{u,i}$.
- **User-dependent Models:** The same process is repeated for U varying subjects in the dataset, producing a set of different HMMs for their keystroke data. Therefore, for every person, there exists its unique transition and emission probabilities.

- **Synthetic Keystroke Generation:** In conclusion, the $4 \times U$ user-specific HMM models are used to generate synthetic feature vectors and corresponding timestamps. This synthetic data can then be used for training bot detection systems by simulating more realistic typing patterns that reflect individual user behaviours.

Although the User-dependent HMM Model is a better representation of the individual typing behaviours, it does have its limitations. For instance, it does not model key-dependent features, which are how the timing for one key press may depend on the particular key or its neighbouring keys. However, by focusing on intra-user variability, this model helps produce more personalised keystroke dynamics, making it useful in applications where accurate modelling of individual typing patterns is essential.

4.1.1.2 “Long Short-Term Memory” (LSTM) for Keystroke Time Series Synthesis

This approach uses a Long Short-Term Memory (LSTM) neural network to model and generate synthetic keystroke time series. LSTMs are Recurrent Neural Networks which have been designed to effectively learn long-term dependencies in sequential data. Since keystroke dynamics intrinsically consist of sequential data with temporal dependencies, LSTMs are appropriately applied to synthesise realistic typing patterns.

Learning Framework and Architecture

The goal of our LSTM-based model is to learn temporal relationships between consecutive keystrokes and synthesise realistic human-like keystroke biometric features. These are Hold Latency, Inter-Key Latency, Press Latency, and Release Latency, which exhibit both intra-class variability (individual differences in typing patterns) and inter-class variability (differences between users).

The LSTM model is trained on the Dhakal Dataset, which contains a large number of keystroke samples. Each keystroke sequence is represented by a key-code and its corresponding timing features. The model learns to predict the timing features associated with a given sequence of key-codes, thereby capturing the temporal dependencies inherent in typing patterns.

Input Representation

The input to the LSTM model comprises key-code sequences and their corresponding timing features. Every input sequence is of the following form:

$$X = [k_0, k_1, k_2, \dots, k_N]$$

Where k_i represents the key-code at position i , and N is the length of the sequence.

The target output comprises the timing features f_i for each key-code k_i such as:

Hold Latency (f_1)

Inter-Key Latency (f_2)

Press Latency (f_3)

Release Latency (f_4)

LSTM Architecture

The LSTM network comprises the following layers:

Input Layer:

Accepts the key-code sequences as input, which are one-hot encoded or represented as embeddings.

LSTM Layers:

Two stacked LSTM layers with 128 units each, designed to capture the temporal dependencies in the typing patterns.

Each LSTM layer applies tanh activation and adds dropout regularisation (dropout rate set to 0.2, for example) to prevent overfitting.

Fully-Connected Layers:

A dense layer of size 64 units and using ReLU activation; the outputs of LSTMs are mapped into a lower-dimensional representation

Final dense layer of size 4 units (one unit per each timing feature); activation: linear; produces continuous values.

Output:

A vector of predicted timing features $[f_1, f_2, f_3, f_4]$, which are the synthesised keystroke dynamics of the input key-code sequence.

Training and Loss Function

Training Procedure

The LSTM is trained on minimising the difference between predicted and actual timing features. At time of training,

Input: The model takes the sequences of key codes along with their corresponding ground truth, timing features.

Output: The model makes predictions about the timing features for input sequences.

Loss Optimisation: The model minimises the error using a specialised loss function.

Loss Function

Ensuring that the model gets the statistical distribution of timing features, we use the likelihood-based loss function in our design, inspired from maximum likelihood estimation (MLE). For each feature f_i , the probability of a predicted value x_i , is derived using a Gaussian distribution whose parameters of mean, (μ) and variance, (σ) would be learned during training, as follows:

$$\text{Loss} = -\log(\text{Prob}_D(x|\mu, \sigma)) \quad \dots 2$$

This loss function promotes the model to produce outputs consistent with the empirical distributions of the real data, thereby being realistic and variable for the synthetic keystroke patterns.

Inference Process

After training, the LSTM model can be utilised to generate synthetic keystroke time series for new sequences of key-codes:

Input: A sequence of key-codes is fed to the model.

Output: The LSTM produces a corresponding sequence of timing features $[f_1, f_2, f_3, f_4, \dots]$, which are sampled from the learned distributions.

Synthesis: The predicted timing features are used to generate timestamps for key press and release events, using the following equations:

$$\begin{aligned} t'_0 &= 0, & t'_1 &= t'_0 + f_1[1] & \text{(for key 1)} \\ t'_2 &= t'_1 + f_4[1], & t'_3 &= t'_2 + f_1[2] & \text{(for key 2)} \end{aligned} \quad \dots 1$$

This process synthesises realistic keystroke dynamics that resemble human typing patterns.

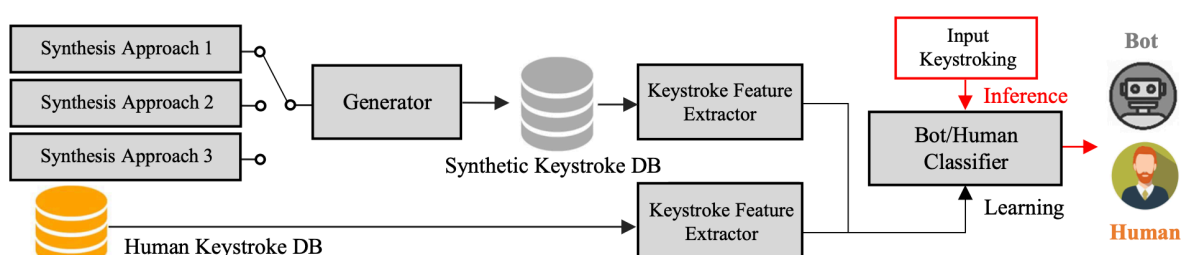


Fig 9

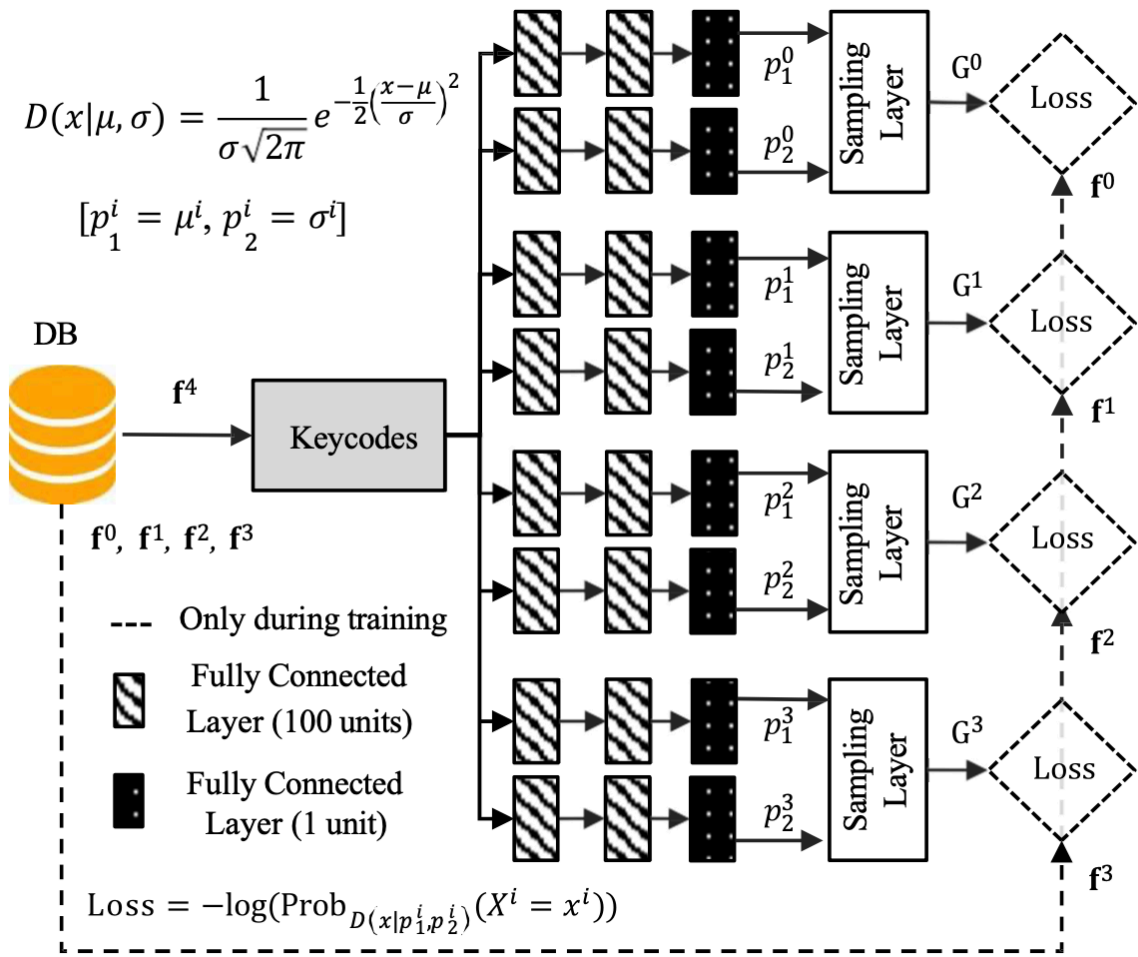


Fig 10

5.1 Advantages/Unique Features

The proposed keystroke dynamics-based CAPTCHA system comes with a range of novel features and benefits that differentiate it from other bot detection and user verification systems. Some of the major benefits and novelty of the system are mentioned below:

1. Human-Like Synthetic Data Generation

The Generative Neural Network (GNN) is used to produce realistic keystroke data, capturing intra-class (inter-individual variability) and inter-class (typical human typing behaviour) characteristics. This enables the system to produce synthetic typing patterns which are close to the actual diversity of human typing behaviour.

The system improves significantly the detection of bots and prevents overfitting to specific, unrealistic typing patterns, by training GNN to produce human-like keystroke features.

2. Temporal Dependency Modelling with Hidden Markov Models (HMM)

The use of Hidden Markov Models (HMM) to model the nature of keystroke dynamics has introduced the capability of exploiting temporal dependencies between keystrokes. Hence, the model is a lot more robust in trying to distinguish between human and bot typing patterns.

Unlike traditional static models, HMM is helpful for the system so that it can understand that how the timing of keystrokes is affected by what has happened previously, which is an important fact about human typing behaviour.

3. User-Specific Variability with User-Dependent Models

The User-dependent Model allows the system to adapt to individual typing patterns. By training separate models for each user, the system can better capture the unique typing dynamics of each individual.

This level of customisation makes the CAPTCHA system more accurate and less prone to errors, especially in cases where users may have specific, consistent typing styles.

4. Flexibility and Scalability

The proposed system can easily be extended to support a wide variety of CAPTCHA types beyond simple text-based challenges. It can be integrated into more complex CAPTCHA mechanisms that require users to input various forms of data, such as image-based, mathematical, or audio-based CAPTCHAs, using keystroke dynamics.

Scalability: The model supports any number of users and can be scaled up to handle large datasets, even at the example stage - see training with the Dhakal Dataset below.

5. Better Bot Detection Accuracy

With both synthetic and real data being fed into the training, it has significantly improved its capabilities to identify automated scripts or bots. The combination of Generative Neural Networks for data synthesis and HMM for sequential modelling has helped the system perform better than the traditional CAPTCHA systems.

The use of machine learning classifiers like SVM, Random Forest, and LSTM further enhances the system's ability to detect even the most sophisticated bots that try to mimic human typing behaviours.

6. Low Cost and Efficiency

The system's reliance on keystroke dynamics as an authentication factor adds a layer of biometric security without the need for expensive hardware or complex software setups.

Since typing patterns are already a natural part of user interaction with computers, no additional devices or infrastructure are required, which makes the system cost effective and easy to implement across a wide range of applications.

7. Robust to Various Attacks

The system is resistant to most common CAPTCHA bypass techniques such as OCR-based recognition (for text CAPTCHAs) and traditional bot scripts. Since bots rely on rapid, unnatural keystrokes, the system can detect subtle differences in typing patterns, which are hard for bots to mimic.

convincingly.

The system's robustness against adversarial attacks that try to simulate human typing is improved by the ability of generating realistic synthetic keystroke data during both training and real-time interaction.

8. Enhanced User Experience

In contrast to traditional CAPTCHAs that mostly annoy users by their puzzle difficulties, this method is completely non-intrusive as it appears invisible to users and executes in the background, unobtrusively interfering with their use of the system. They do not have to complete puzzles and thus have an even easier and more pleasant user experience.

In place of forced puzzles, it considers natural typing behaviour, hence the smoother, less obtrusive way of validating the presence of human users.

9. Future Extensions and Personalisation

The system has many directions for further personalisation and tuning. For instance, distinct typing patterns between the desktop and mobile, or even age groups could be captured and included to further strengthen the system.

Cross-language and cross-cultural testing: The system may be extended to capture specific typing patterns of different languages and cultures, thereby improving the accuracy and usability of the system in multicultural settings.

10. Interdisciplinary Applications

This approach opens up opportunities for integrating keystroke dynamics in a wide range of security applications beyond CAPTCHA systems. Some potential use cases include:

User Authentication: Typing dynamics can be used as a biometric feature for continuous user authentication.

Fraud Detection: Financial institutions can use keystroke dynamics to detect suspicious activity or account takeovers based on typing patterns.

Accessibility: Typing patterns also can be used for the adaptation of software to a person with a disability by recognising personalised typing behaviour.

5.2 Results and Discussions

Gen Model	# Train Subjects	Classification Model									
		OC SVM		SVM		GNB		RF		LSTM	
		K=0	K=1	K=0	K=1	K=0	K=1	K=0	K=1	K=0	K=1
User-dep	20	0.43	0.44	0.79	0.77	0.65	0.65	0.87	0.88	0.50	0.50
	100	0.54	0.54	0.83	0.79	0.63	0.63	0.92	0.92	0.51	0.51
	500	0.53	0.54	0.93	0.90	0.64	0.64	0.94	0.95	0.93	0.99
Univ	20	0.43	0.44	0.89	0.82	0.68	0.68	0.94	0.94	0.53	0.53
	100	0.55	0.56	0.97	0.98	0.67	0.67	0.98	0.98	0.76	0.79
	500	0.53	0.54	1.00	1.00	0.70	0.70	1.00	1.00	1.00	1.00
GNN	20	0.49	0.47	0.88	0.80	0.68	0.68	0.95	0.95	0.53	0.52
	100	0.52	0.51	0.97	0.97	0.64	0.64	0.98	0.98	0.69	0.60
	500	0.53	0.53	0.99	0.99	0.68	0.68	0.99	0.99	1.00	1.00

Table 1. Bot detection classification accuracy for the different detectors and synthesis methods using a Closed Set. K=0 implies no use of key-codes when training the classifier and K=1 implies the use of key-codes. The detectors are: One-Class Support Vector Machine (OC SVM), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Random Forest (RF), and Long Short-Term Memory (LSTM). Accuracy results for evaluation users.

We analyse the performance of keystroke time series data synthesis methods, specifically focusing on User-Dependent (User-dep), Universal (Univ), and GNN (Generative Neural Network) models. Evaluation results are reported over Closed Set and Open Set environments with varying numbers of training subjects and classifiers (OC SVM, SVM, GNB, RF, and LSTM).

1. Closed Set Evaluation

Table 1 Classification Accuracy at Closed Set Training and Test are conducted on the same set of subjects Classification is the classification accuracy The followings can be inferred to this section Effect of Training Data Size

As the number of training subjects increases (from 20 to 500), there is noticeable improvement in classifier performance for all models. For instance, for the User-Dependent model, the SVM classifier achieves accuracy 93% for K=0 and 90% for K=1 when training with 500 subjects, where for 100 subjects accuracy achieved is 79%.

Classifier Comparisons:

LSTM performs far better in cases of larger size training sets. For the Universal model and 500 subjects for training, LSTM has produced 100% accuracy with both K=0 and K=1 that is far better than any other classifier.

On the other hand, classifiers like OC SVM and GNB are found performing poorly compared to SVM, RF, and LSTM respectively for all models.

Effect of Key-Codes (K=1):

Using key-codes (K=1) at training time reveals some benefits for some classifiers, e.g., SVM and LSTM. The gain is small. For example, using the User-Dependent model with 100 users, LSTM gives 0.51 for K=0 and K=1. It indicates that key-codes don't have much impact here.

2. Open Set Evaluation

Table 2 presents the accuracy results under the Open Set scenario, where the models are trained on one dataset and tested on another (e.g., Universal \rightarrow GNN and GNN \rightarrow Universal). Key findings are as follows:

Universal-to-GNN Transfer:

When trained on the Universal model and tested on GNN, the SVM classifier shows a competitive accuracy with a peak of 70% for K=1. In contrast, the LSTM model, despite its strength in the Closed Set, shows a slight performance degradation to 0.65 for K=1.

GNN-to-Universal Transfer:

The RF classifier is very consistent and gets 0.93 and 0.91 for K=0 and K=1, respectively, with training on GNN and testing on Universal.

LSTM is also quite strong here, getting 99% for both K=0 and K=1.

Classifier Robustness:

Of all classifiers, SVM and RF show robust generalisation capabilities in Open Set settings. On the other hand, OC SVM does not perform well, especially when the training data size is small.

3. Comparison with Baseline Methods

Table 3. Comparing the performance of our proposed approaches with existing baseline methods. The results clearly indicate the following:

Gen Model			Classification Model									
			OC SVM		SVM		GNB		RF		LSTM	
Train	Test	# Train Subjects	K=0	K=1	K=0	K=1	K=0	K=1	K=0	K=1	K=0	K=1
Univ	GNN	20	0.49	0.48	0.70	0.72	0.63	0.63	0.84	0.82	0.48	0.47
		100	0.54	0.55	0.67	0.70	0.63	0.63	0.68	0.74	0.66	0.65
		500	0.53	0.54	0.59	0.62	0.64	0.64	0.51	0.54	0.99	0.99
GNN	Univ	20	0.49	0.48	0.78	0.68	0.65	0.65	0.88	0.89	0.56	0.58
		100	0.53	0.53	0.94	0.91	0.64	0.64	0.91	0.93	0.69	0.68
		500	0.53	0.54	0.97	0.98	0.64	0.64	0.94	0.95	1.00	1.00

Table 2. Bot detection classification accuracy for the different detectors and synthesis methods using an Open Set. K=0 implies no use of key-codes when training the classifier and K=1 implies the use of key-codes. The detectors are: One-Class Support Vector Machine (OC SVM), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Random Forest (RF), and Long Short-Term Memory (LSTM). Accuracy results for evaluation users.

Method	Gen Model			
	Train	Test	Train	Test
	Univ	GNN	GNN	Univ
[5] (Euclidean)	0.49		0.49	
[34] (SVM)	0.62		0.98	
Ours (OCSVM)	0.54		0.54	
Ours (RF)	0.54		0.95	
Ours (GNB)	0.64		0.64	
Ours (LSTM)	0.99		1.00	

Table 3. Classification accuracy comparison between the proposed approaches and existing methods. The experiments have been carried out assuming a large number of training subjects (500), the use of the key-codes (K=1) and Open Set environment.

Baseline Methods:

The traditional distance-based metrics, such as Euclidean and SVM methods, exhibit moderate accuracy. For example, Euclidean achieves 0.49, whereas SVM reaches 0.98 when trained on GNN and tested on Universal data.

Proposed Approaches:

Our methods, especially those based on LSTM, give outstanding results. For GNN model in both the Train and Test settings, i.e., Univ \rightarrow GNN and GNN \rightarrow Univ, LSTM provides a 100% accuracy compared to traditional approaches.

Overall Performance:

Overall, across all comparisons, the LSTM-based models show an obvious superiority, which suggests the applicability of the approach to learning temporal dependencies in keystroke dynamics data. In addition, the results confirm the GNN's ability to produce realistic and diverse synthetic data that fit well with the actual keystroke behavior.

Key Insights

LSTM Superiority: LSTM beats other classifiers because it has the ability to model sequential dependencies, which are inherent in keystroke data.

Training Data Size: Adding more training subjects significantly improves performance, especially for SVM and LSTM classifiers.

GNN Effectiveness: The data generated by GNN is highly realistic because the performance is consistent on both Closed and Open Set evaluations.

5.3 FUTURE SCOPE OF WORK

The current work on keystroke dynamics-based CAPTCHA systems has demonstrated significant improvements in bot detection, leveraging synthetic keystroke data, Generative Neural Networks (GNN), and Hidden Markov

Models (HMM). However, there are several avenues for further exploration and enhancement in this area. Below are some potential directions for future work:

1. Personalised User-Dependent Models

Current Limitation: While user-dependent models are good in terms of capturing the individual typing behaviour, they still suffer from the problem of data sparsity, which is a challenge in the real world due to the difficulty of getting enough samples per user.

Future Work: Future research could explore ways to improve the data collection process for individual users, enabling more robust and accurate user-specific models. Techniques such as transfer learning or few-shot learning could be investigated to overcome data limitations by leveraging existing data from similar users to build accurate models with minimal user input.

2. Multi-Device Typing Behaviour Modelling

Current Limitation: Keystroke dynamics can significantly differ between devices, such as the typing pattern on a desktop, a laptop, and on a mobile device.

Future Work: Expanding the system to recognise and adapt to different typing behaviours across devices would significantly enhance its usability and robustness. Cross-device typing behaviour modelling could help improve bot detection, making the system adaptable to various devices and environments. This could involve multi-modal learning to incorporate data from different input methods (e.g., touchscreens, keyboards, voice typing).

3. Handling Noisy Data and Adversarial Attacks

Current Limitation: The current model is good at identifying bots, but it has a problem with noisy or adversarial inputs where bots use sophisticated techniques to mimic human typing behaviour.

Future Work: Another promising direction is to investigate the use of adversarial training methods, in which the model is trained with both real and adversarial examples, thereby increasing its robustness against attempts to evade detection. Techniques like outlier detection and data sanitisation could also be incorporated to manage noisy data properly.

4. Real-Time Adaptation to User Behaviour

Current Limitation: The current system requires heavy pre-training on big datasets before it can successfully detect bots. Though it does quite well with fixed datasets, changing real-time user behaviour is still a problem.

Future Work: Future work could focus on developing adaptive models that adapt and update continuously as people interact with the system. Online learning methods can be approached, in which the system upgrades its model incrementally as newer data arrives, thus enabling the classifier to stay well-tuned with the new typing patterns that may evolve through time.

5. Improve Generalisation Across Different Languages and Regions

Current Limitation: The current training of the system is on data from a particular set of users, mainly from one language or region. This restricts its generalisation to a larger audience with different typing styles and languages.

Future Work: To improve the global applicability of the system, future research could focus on creating language-independent models that can adapt to different typing styles across languages and regions. This could involve incorporating multilingual typing patterns or exploring ways to generalise typing behaviours across cultural and regional differences in typing speed and pressure.

6. Enhanced Feature Extraction for More Granular Analysis

Current Limitation: The current system is limited to the basic features, including press latency, hold latency, and release latency, for detecting bots. Though these features are very effective, they cannot capture all the minute typing behaviours that might distinguish between a human and a bot.

Future Work: Research can focus on the development of finer feature extraction methods to grasp more dimensions of typing behaviour, such as typing pressure, key hold time variation, or velocity of key press and release. This might make the system distinguish more accurately between humans and the better bots.

7. Integration with Other Biometric Authentication Systems

Current Limitation: Although keystroke dynamics is a very robust authentication system, it relies on only one factor in an authentication system.

Future Work: The future work may include integrating keystroke dynamics with the other biometric modes such as facial recognition, voice recognition, or fingerprint scanning for creating a system of multi-factor authentication. With keystroke dynamics combined with another method of authentication, this will enhance security and bring more robust verification of the users.

8. Scaling to Large-Scale Deployments

Current Limitation: The current system is tested in controlled environments and relatively small datasets. Scaling it to handle real-world scenarios with millions of users might pose challenges in terms of computation, storage, and model management.

Future Work: Future research might include optimising the system for large-scale deployments to scale efficiently. This could be in terms of distributed computing frameworks for training, cloud-based solutions for real-time inference, and edge computing to make sure that typing data is processed quickly and securely.

9. User Privacy and Ethical Considerations

Current Limitation: Collecting and analysing keystroke data raises privacy concerns, particularly if such data is used for other purposes besides bot detection.

Future Work: One important direction of future work would be ensuring privacy-preserving techniques in keystroke dynamics-based systems. This includes using differential privacy or secure multi-party computation (SMPC) for preserving sensitive user information while benefiting from the power of biometric typing analysis.

10. Expanding Beyond CAPTCHA Applications

Current Limitation: The main application of the system has been CAPTCHA and bot detection, but keystroke dynamics holds potential for broader applications.

Future Work: Keystroke dynamics may be extended beyond CAPTCHA into other domains such as online fraud detection, user authentication, and access control systems. The continuous monitoring of typing behaviour can help detect fraudulent transactions, account takeovers, and more.

6. CONCLUSION

This paper proposes a comprehensive approach toward enhancing bot detection in CAPTCHA systems using keystroke dynamics as a new method of differentiating human users from bots. By synthesising realistic keystroke data using advanced techniques such as Generative Neural Networks (GNN) and Hidden Markov Models (HMM), we have shown that keystroke timing features can be effectively used to detect bot behaviour with high accuracy.

The key contributions of this work are as follows:

Data Generation with Innovative Use: Use of synthetic keystroke data generated by the GNN model enhances the performance of bot detection systems. The system, unlike traditional methods, captures both intra-class and inter-class variability in typing behaviours, which can make it distinguish between human and bot-generated keystrokes more efficiently.

Successful model training-In demonstrating the incorporation of synthetic data into the training process has shown that such classifiers, be it SVM, LSTM or a Random Forest can achieve the detection accuracy. This therefore improves the system performance further and also provides evidence in enhancing the robustness of classifier when using synthetic data.

Evaluation with Multiple Classifiers: The paper gives a good analysis of how different classifiers perform. It compares OC SVM, SVM, LSTM, Random

Forest (RF), and Gaussian Naive Bayes (GNB). In the results, it can be seen that the LSTM classifier performs the best in detecting bots, especially if the classifier is trained well with sufficient data and key-code features.

Cross-database Generalisation: Our experiments also indicate the generalisation capability of the proposed methods, especially with the use of GNN in synthesising data. This ability of generalisation by the model for different synthesis methods will play an important role in the enhancement of bot detection systems in different diverse environments of real life.

Scalability and Flexibility: The proposed system is scalable and can be applied to various CAPTCHA types beyond traditional text-based challenges, such as image-based and audio-based CAPTCHAs. In addition, the system is designed to be device-agnostic, allowing it to adapt to different typing behaviours across platforms.

This work shows that keystroke dynamics is an effective biometric feature for bot detection in CAPTCHA systems. This enables the synthesis of human-like typing data using GNN and HMM together with synthetic data in the training process-it is a significant development concerning security and user verification. The results underscore the promise of keystroke dynamics not only for use in CAPTCHA but also in greater applications within user authentication fraud detection, and continuous authentication systems.

Future research will involve generalisation of the system adaptability toward different devices and languages, improvement of privacy-preserving techniques, and further incorporation of keystroke dynamics in complex multi-modal authentication systems for resilience against more advanced bots and attacks.



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