



Determine a Performance Parameter by Using the IOTA Distributed Ledger Technology Method

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ABSTRACT:

This study aims to improve execution time, CPU utilization, network efficiency, and scalability while upholding robust security measures. The IOTA-DLT-based RA-WRW algorithm is developed in Python, considering node resources and transaction weights for optimal tip selection—verification procedures confirming tip authenticity and transaction validity.

The algorithm significantly improves IOTA network transaction processing efficiency tips exhibit high authenticity and consistency, affirming the algorithm's effectiveness.

The research presents the innovative IOTA-DLT RA-WRW algorithm, which integrates Resource Allocation (RA) and Weighted Random Walk strategies. This novel approach tackles challenges like lazy tip selection, network congestion, and double spending. By performance parameter and the tip selection process, the algorithm improves comparative analyses against existing methods and confirms the superior performance of our model, boasting high accuracy, f-measure, recall, precision, and scalability in distributed ledger transactions, significantly enhancing the IOTA network's transaction processing capabilities.

Keywords: IOTA, DLT, Transaction datasets, transaction weights, random walk, tip selection, private key.

1. Introduction

In applications such as smart cities, homes, automobiles, and healthcare, the Internet of Things (IoT) connects many devices for data exchange, necessitating rapid connectivity, low latency, and high throughput [1]. Through established, interoperable communication protocols, the Internet of Things (IoT) is a worldwide information system of decentralized devices that can identify, sense, and process data [2]. It can greatly improve living standards and financial circumstances [3]. Functionalities like permission and access control are crucial for the broad adoption of IoT systems [4]. The industry must create systems that can manage a high volume of microtransactions while preserving data integrity as IoT technologies progress [5]. The goal of the IOTA project is to link IoT devices in a completely decentralized network[6]. It



represents a decentralized, open-access ledger utilizing a directed acyclic graph (DAG) structure called the "tangle" for storing individual peer-to-peer transactions that are interconnected yet distinct [7]. It is designed as a public distributed ledger for fee-free microtransactions, addressing scalability and fee issues found in traditional distributed ledgers [8]. Unlike blockchain-based alternatives, IOTA utilizes a Directed Acyclic Graph (DAG) called the Tangle to store transactions, enhancing scalability [9]. Operating as a peer-to-peer network, IOTA offers a tamper-evident, collectively maintained digital ledger [10].

Distributed Ledger Technologies (DLTs), such as IOTA, enable untrusted parties to reach consensus across decentralized networks [11], providing transparency, redundancy, and accountability [14]. DLTs are classified into three major types: Blockchain, IOTA Tangle (DAG), and Hash graph [12]. They are recognized for their potential in Cyber-Physical Systems (CPS) like IoT, facilitating the logging and validation of transactions without a centralized authority [13]. In recent years, developments in DLTs, which provide consensus procedures among several untrusted parties, have led to their widespread application in interconnected networks of devices [15]. The IOTA protocol sets itself apart from conventional distributed ledger protocols through its unique numerical system [16]. The emergence of blockchain technology, a form of distributed ledger technology, has generated high expectations for more sustainable agricultural systems and practices across various aspects of the triple bottom line [17].

Despite these advancements, the IOTA network faces challenges in optimizing transaction processing efficiency, particularly concerning execution time and CPU usage. Efficient transaction processing is crucial for maintaining the performance and scalability of IoT systems. While several DLT-based solutions like IOTA+ROS 2 architecture [18], One IOTA of Countless Legions (OICL) [19], and a Lightweight Authentication Scheme using IOTA in IoT Platforms (LASII) [20] have been proposed, an optimal solution has yet to be found. Therefore, it is essential to develop an efficient IOTA-based network to improve the scalability and efficiency of the system. (Vyas, Resource allocation strategies for improved IOTA performance using in IoT using DLT, 2024)

This study aims to optimize IOTA network transaction processing by introducing a novel IOTA-DLT-based RA-WRW algorithm. The objectives include improving execution time, CPU utilization, network efficiency, and scalability while upholding robust security measures. In this research, it introduces a novel model based on DLT to address these challenges. The model leverages a Resource Allocation with a Weighted Random Walk (RA-WRW) algorithm designed to optimize the tip selection process by considering node resources and transaction weights. By improving the execution time and CPU utilization, the proposed model aims to significantly enhance the efficiency and scalability of the IOTA network.



The main contribution of the proposed is summed up as follows:

- Initially, the transaction datasets utilizing IOTA are gathered from conventional online sources.
- As a result, the system imports transaction data, undergoing a preprocessing phase where noise data, null values, and error features are removed.
- The processed dataset is then moved to the feature extraction stage, which derives the different features like transaction amount, timestamp, transaction ID, sender and receiver addresses.
- Then, the novel Distributed Ledger Technology based Resource Allocation Weighted Random Walk (IOTA-DLT based RA-WRW) is designed in a PYTHON environment. It aims to optimize the tip selection process by considering both the available resources of nodes and the weights assigned to transactions.
- The extracted features are then authenticated by sign the transaction using the sender's private key.
- Following that, the proposed Resource Allocation based Weighted Random Walk algorithm is used for the tip selection in IOTA tangle to improve execution time, optimize CPU usage, enhance network efficiency, and increases the scalability and the algorithm aims to achieve faster transaction confirmations.
- The authenticity and consistency of the chosen tips are then confirmed during the verification process. Moreover, to check the format and content of the chosen tips, as well as the transaction fields, references to previous transactions, and other pertinent data.
- Subsequently, Security analysis assess the overall security and trustworthiness of the IOTA network and analyse the resilience against various attack vectors.
- Finally, the system's robustness in terms of recall, precision, and accuracy, F-measure, Confirmation Time, Computation Time, Time Complexity, execution time and CPU usage were computed.

The research's subsequent segment can be succinctly outlined as follows: Section 2 delves into a relevant review of existing literature, while Section 3 formulates the system model and articulates the problem statements. The proposed framework is subsequently elucidated in Section 4, and the results are presented and juxtaposed in Section 5. The paper concludes in Section 6.

2. Related work

Farahani et al. [21] presented a comprehensive reference architecture for the intersection of blockchain and IoT, highlighting advancements and challenges. Despite its potential for new



applications, the energy-intensive nature of consensus mechanisms like Proof-of-Work (PoW) and the resource constraints of IoT devices pose significant drawbacks.

Shahid et al. [22] introduced WOTS-S, a hash-based One-Time Signature scheme tailored for post-quantum cryptographic currencies. Although it offers a secure alternative to ECDSA in a post-quantum world, its large signature sizes are impractical for distributed ledgers in IoT scenarios.

To address these concerns, Shahid et al. [23] developed Smart Digital Signatures (SDS), an efficient upgrade to the XMSS hash-based approach, reducing key generation and signature formation times by 70% and 60%, respectively. However, its reliance on technological infrastructure introduces potential points of failure, raising concerns about system dependability.

Wang et al. [24] proposed a trust mechanism for consensus protocols in Industrial IoT (IIoT), using a reputation module to enhance global reputation understanding during consensus. While efficient and safe, the lack of encryption poses a risk of exposing logged information.

Zhao et al. [25] designed a secure sensing data processing and logging system using blockchain technology for immutable data storage, eliminating the need for third-party authenticator connections. Despite its robustness, the system's limited range remains a significant drawback.

Anglés-Tafalla et al. [26] introduced a decentralized management strategy for Low Emission Zones (LEZs), treating vehicle accesses as blockchain transactions and using smart contracts for pricing. Although effective in controlled environments, LEZs can inadvertently create high emission zones elsewhere.

Scheid et al. [27] developed a process improvement framework for business continuity (BC), utilizing Policy-based administration (PBM) for detailed BC transactions. This approach simplifies data management but can increase development complexity.

Alavizadeh et al. [35] proposed the Multiple Coordinator Selection (MCS) algorithm to enhance IOTA's security and reliability by involving multiple coordinators based on metrics such as trust and node activity. While improving system security and transaction distribution, the complexity of managing multiple nodes is a notable drawback.

Misbah Khan et al. [36] introduced a discrete-event simulator for IOTA's Tangle protocol to analyze transaction dynamics and node convergence. Although the simulator provides valuable insights, its technical setup and parameterization can limit accessibility for less experienced users.

The IOTA-DLT based RA-WRW algorithm optimizes execution time and CPU usage in the IOTA network by efficiently managing node resources through a strategic resource allocation



approach. Unlike energy-intensive PoW mechanisms, it utilizes a weighted random walk for tip selection, which enhances transaction confirmation efficiency and scalability while ensuring robust security without requiring large signature sizes. The method includes comprehensive preprocessing and feature extraction steps to maintain data integrity and reliability, thereby mitigating potential single points of failure. Additionally, an authentication and verification process enhances transaction trustworthiness, addressing encryption concerns. Overall, this research improves the performance, scalability, and applicability of the IOTA network in IoT scenarios, overcoming existing methodological limitations.

Table 1: Existing Work Challenges

Sl.No	Author	Method	Advantage	Disadvantage
1.	Farahani <i>et al.</i> [21]	Holistic Reference Architecture	Often resource-constrained and operate on limited battery power	Energy requirements
2.	Shahid <i>et al.</i> [22]	WOTS-S	Hash-based signature schemes offer a compelling alternative to ECDSA	Relatively larger signature sizes
3.	Shahid <i>et al.</i> [23]	Smart Digital Signatures (SDS)	It outlines a strategy for integrating SDS into a decentralized ledger system, leveraging HLPN for implementation.	Reliance on technology introduces a potential single point of failure
4.	Wang <i>et al.</i> [24]	Trust scheme for consensus protocol	It has a good performance for efficiency and safety	Risk of exposing the information recorded through data logging, Lack of encryption
5.	Zhao <i>et al.</i> [25]	A robust system for processing and logging secure sensing data	Inspired and enabled by the blockchain technology.	It has a limited range.
6.	Anglés-Tafalla C <i>et al.</i> [26]	LEZ (low emission zone) management	Decentralized proposal is lightweight and feasible	They produce high emissions zones



7.	Scheid <i>et al.</i> [27]	A novel refinement flow	Simplifies data management in multiple BCs	Potentially increase the complexity
8.	Alavizadeh, <i>et al.</i> [35]	Multiple Coordinator Selection (MCS) algorithm	improved system security, reduced collusion risks, and better transaction distribution	It increased complexity in managing and coordinating multiple nodes.
9.	Misbah Khan <i>et al.</i> [36]	discrete-event simulator design for IOTA's Tangle protocol	Valuable insights into transaction dynamics	Technical setup limits accessibility

(Vyas, Resource allocation strategies for improved IOTA performance using in IoT using DLT, 2024)

3. SYSTEM MODEL AND PROBLEM STATEMENT

The system utilizes the IOTA distributed ledger technology (DLT) platform, which consists of a network of nodes actively participating in transaction processing, ledger maintenance, and smart contract execution. Each node in the network is equipped with computational resources such as CPU, memory, and storage. The objective is to measure and optimize the execution time and CPU usage of transactions and smart contracts on the IOTA network.

Problem Statements:

- **Execution Time:** Transactions in the IOTA network experience delays due to the inefficiency of the tip selection process.
- **CPU Usage:** High CPU utilization during transaction processing limits the network's scalability and performance.
- **Scalability:** The system's performance degrades as the number of transactions or the complexity of smart contracts increases.
- **Lazy Tip Selection:** Inefficient tip selection by nodes leads to longer confirmation times and affects overall network performance.
- **Network Congestion:** The network faces congestion issues when transaction volumes exceed processing capacity, causing delays and increased CPU usage.

The proposed methodology optimizes execution time by implementing the RA-WRW algorithm, which enhances the tip selection process, resulting in faster transaction and smart contract confirmations. By efficiently allocating resources, the overall CPU usage is reduced,



allowing the network to handle a greater number of transactions and more complex smart contracts simultaneously. This systematic approach to measurement and optimization ensures that the system maintains high performance and scalability, even as transaction volumes and complexities increase. Additionally, optimizing tip selection mitigates lazy tip selection, reducing confirmation times and improving network performance, while comprehensive analysis of CPU usage helps alleviate network congestion.

4. PROPOSED METHODOLOGY

A novel Internet of Things Application with IOTA DLT-based Resource Allocation with Weighted Random Walk (IOTA-DLT based RA-WRW) strategy was designed to optimize the tip selection process by considering both the available resources of nodes and the weights assigned to transactions and to improve the execution time and CPU usage by IOTA. IOTA represents a decentralized ledger technology and digital currency specifically designed for the IoT landscape. It offers a scalable and safe framework for facilitating IoT device transactions.

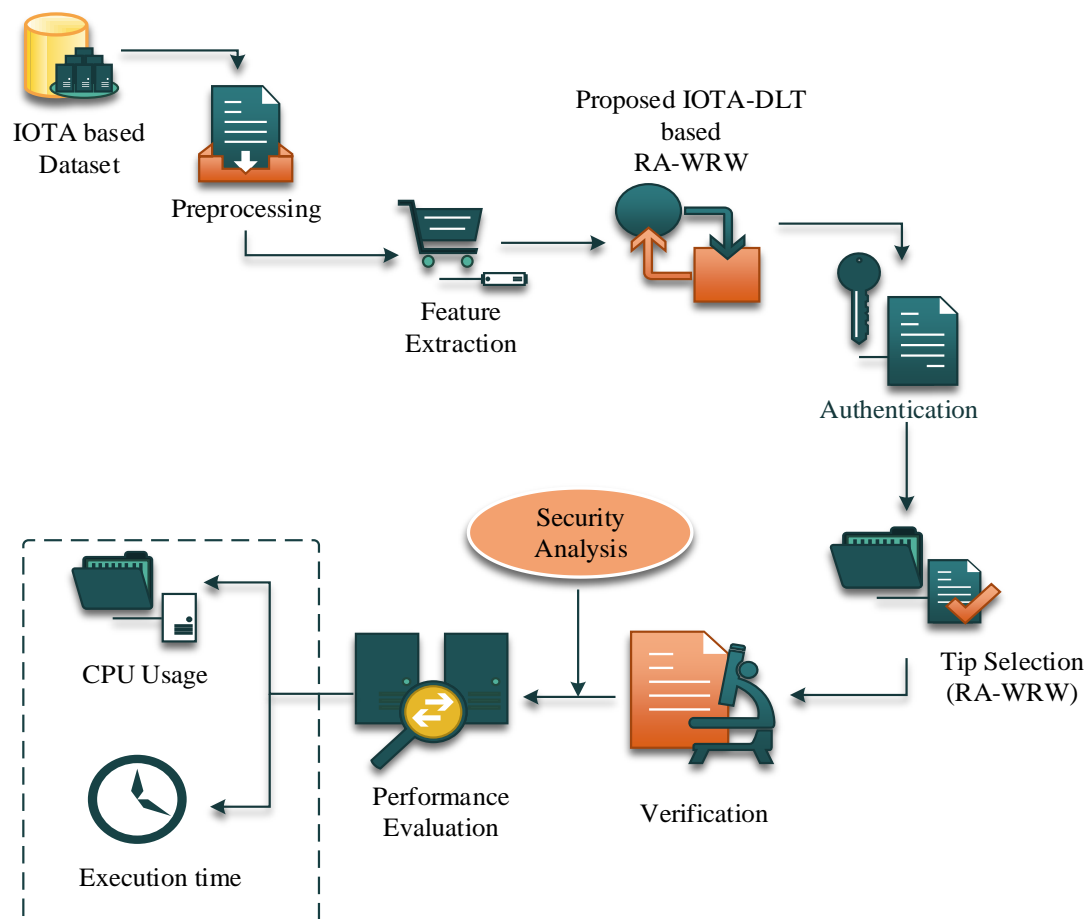


Figure 2: Proposed architecture of IOTA-DLT based RA-WRW



The IOTA datasets are collected from web sources and imported into the system for preprocessing. This phase involves filtering noise data, handling null values, and correcting errors. Features such as transaction amount, timestamp, transaction ID, sender and receiver addresses are extracted in the subsequent stage. The Distributed Ledger Technology based Resource Allocation with Weighted Random Walk (IOTA-DLT RA-WRW) is implemented in PYTHON to optimize tip selection by considering node resources and transaction weights, facilitating secure and scalable IoT device transactions.

Extracted features undergo authentication via transaction signing using the sender's private key. The Resource Allocation based Weighted Random Walk Algorithm is then applied to improve execution time, CPU usage, network efficiency, and scalability by accelerating transaction confirmations. The chosen tips' authenticity and consistency are verified, ensuring correct format, content, transaction fields, references to previous transactions, and other relevant data.

Security analysis assesses IOTA network security and resilience against various attack vectors. System robustness is evaluated based on scalability, precision, recall, accuracy, F-measure, execution time, and CPU usage.

4.1 IOTA based dataset:

During initialization, In IOTA the transaction data are collected from the standard website. In IOTA a data structure known as a bundle serves as the representation of a payment. Address, signature, value, and tag fields are included in IOTA transactions. A valid payment involves many transactions, which are more like inputs and outputs in IOTA. The data initialization function is used within the system to initialise the dataset. Eqn. (1) uses to express it.

$$I(td^*) = (g_1, g_2, g_3, \dots, g_n) \quad (1)$$

Where I represent the dataset initialization function, td^* represent the collected IOTA dataset, g denote the information within the IOTA dataset, while n represents the overall quantity of data encompassed by the dataset.

4.2 Preprocessing:

The collected transaction data undergo preprocessing to eliminate noise, null values, and errors. This ensures the raw IOTA dataset is cleaned and formatted correctly for digital currency transactions. Steps include removing unnecessary characters and ensuring consistent formatting to standardize data representation. Verifying the accuracy and legitimacy of sender and receiver addresses is crucial to secure and accurate fund delivery. This preprocessing step enhances system efficiency and reduces computation time. It is calculated using Eqn. (2)



$$P'' = [I(td^*) - \eta(td)] \quad (2)$$

Here, P'' represents the preprocessing function and $\eta(td)$ indicate the presence of disruptive elements within the input dataset.

4.3 Feature Extraction:

Feature extraction involves extracting relevant metadata from IOTA transaction data, such as timestamps, transaction amounts, input and output addresses, digital signatures, and branch and trunk transactions. The timestamp provides transaction generation information, enabling analysis of transactional patterns, confirmation times, and network performance evaluation. The digital signature validates transaction integrity and ensures transactions have not been tampered with. These features are crucial for transaction analysis, network performance assessment, security audits, and monitoring transaction flow within the IOTA network. Here the features are extracted by using the below equation.

$$F'' = [P'' - \lambda(td)] \quad (3)$$

Where the F'' represents the feature extraction function, P'' indicates the wanted features and $\lambda(td)$ denotes the unnecessary features.

4.4 Design of IOTA-DLT based RA-WRW:

IOTA DLT:

The IOTA technology diverges from conventional blockchain by using a novel DLT designed to overcome high transaction fees and slow processing times. The Tangle, built on a Directed Acyclic Graph (DAG), stores and tracks transactions. Tailored for IoT ecosystems, it enables scalable and secure transactions among IoT devices. Transactions in IOTA follow a three-step process: signing, selecting tips, and Proof of Work (PoW). In a fully connected node network, transactions is flow between any pair of nodes, synchronized to read and broadcast transactions in rounds, following the Tangle protocol. The network topology resembles a complete graph.

The DAG:

The Tangle serves as the foundational structure of IOTA, functioning as a DAG responsible for storing transactions. Transactions, represented as vertices or "sites," have two parent vertices and must confirm them to be added. Confirmation extends to all sites confirmed by their parents. A "tip" is an unconfirmed site, and a "Genesis" site lacks parents but is confirmed by all others. When a new transaction enters the Tangle, it endorses two prior transactions, adding two new edges to the graph. Confirmed transactions are broadcasted across nodes.

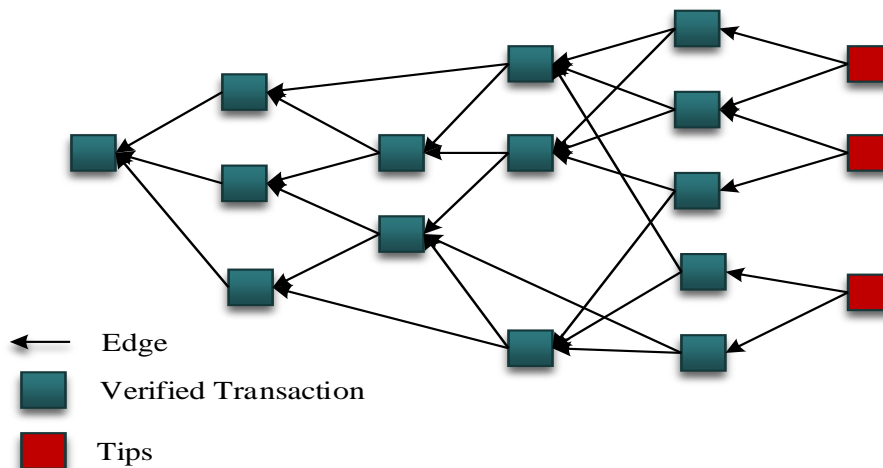


Figure 3: The IOTA Tangle

4.5 Authentication:

To authenticate transactions within the IOTA network, the process begins with transaction signing. The sender uses the private key to generate digital signatures, ensuring the authenticity and integrity of the transaction data. Next, the subseed is calculated by hashing a combination of the sender's seed and key index, following the formula [28]:

$$\text{Subseed} = H(\text{seed} + \text{key index})$$

From the subseed, a private key is derived and undergoes multiple rounds of hashing. This process culminates in the generation of a unique public key address. This address serves as the sender's identity on the IOTA network, enabling them to send and receive transactions securely. Through these steps, the authentication process in IOTA guarantees that transactions originate from the rightful sender and remain tamper-proof, ensuring the network's security and integrity.

4.6 Tip Selection:

After a transaction is authenticated in the IOTA Tangle, the tip selection process begins using the Resource Allocation based Weighted Random Walk (RAbWRW) algorithm. This algorithm takes into account transaction weights, cumulative weights, and connectivity to identify tips (unconfirmed transactions) that are more likely to be successfully confirmed. The process is optimized by considering the network's computational resources, giving higher priority to nodes with more available resources or lower load, thus ensuring efficient use of resources and faster confirmation times.

The algorithm performs a weighted random walk through the Tangle, where the probability of moving from one node to another is determined by their cumulative weights. The cumulative



weight of a node x is calculated as the sum of the weights from all nodes z that directly or indirectly confirm it

$$\text{Cumulative Weight} = \sum_{Z \Rightarrow x} W_z + W_A \quad (4)$$

The separation probability P_{xy} for each step taken by the walker from the current node x to a potential next node y is given by: [29]

$$P_{xy} = \exp(-\alpha(K_x - K_y)) \left(\sum_{Z \Rightarrow x} \exp(-\alpha(K_x - K_z)) \right) \quad (5)$$

where K represents the cumulative weight, α is a positive integer, and $Z \Rightarrow x$ denotes all nodes z that indirectly confirm node x .

For each incoming transaction, the algorithm uses the above equations to calculate the cumulative weight and separation probability. Nodes with higher cumulative weights have a higher probability of being selected as tips. Once the random walk identifies two suitable tips, the new transaction is linked to these tips, confirming them. This newly confirmed transaction is then broadcast to the network, becoming a new tip awaiting further confirmation.

This method ensures efficient and secure transaction confirmations, maintaining the integrity and performance of the IOTA Tangle by prioritizing nodes with more resources and higher cumulative weights, thus optimizing the tip selection process.

4.7 Verification:

After the tip selection, the verification process begins by detecting any conflicts to prevent double-spending, ensuring that no two transactions attempt to spend the same funds. The structure and content of the selected tips are validated, including verifying all necessary fields and checking digital signatures using the public keys derived during authentication.

The cumulative weight of the selected tips is calculated to confirm they have sufficient endorsement from other transactions. The consistency of the references to previous transactions is checked to ensure that the tips are valid and correctly linked within the Tangle.

Once all these checks are passed, the new transaction is added to the Tangle, confirming the selected tips, and is broadcast to the network, becoming a new tip awaiting further confirmation. This comprehensive verification process ensures the integrity and reliability of the IOTA network, maintaining its security and preventing fraudulent activities.

4.8 Security Analysis:



During this stage, perform an in-depth examination of the security aspects of the authentication procedure, encompassing the utilization of private keys and digital signatures. It also assesses the overall security and trustworthiness of the IOTA network and analyze the resilience against various attack vectors. If any potential vulnerabilities, risks, and security-related aspects are identified the transaction will be canceled to mitigate the risks.

Algorithm.1 Proposed IOTA-DLT-based RA-WRW

Start

{

Dataset Initialization()

{

int I, td^*, g_1, \dots, g_n ;

// initialize the IOTA dataset

$I(td^*) = (g_1, g_2, g_3, \dots, g_n)$; //using eqn.(1)

}

Pre-processing ()

{

int P'', I, td^*, η, td ;

$P'' = [I(td^*) - \eta(td)]$; //using eqn.(2)

//then the collected data is preprocessed to neglect noise data and null values

}

Feature Extraction()

{

int $F'', \lambda(td)$;

$F'' = [P'' - \lambda(td)]$; //using eqn.(3)

//after that the relevant metadata is extracted

}

Authentication ()

{

//here the transaction begins by signing

$Subseed = H(seed + key\ index)$;

// Next, the subset is calculated to derive a unique public key address through multiple rounds of hashing.

}

Tip Selection ()

{



```
int  $W_A, W_Z, P_{xy}, \alpha, K_x, K_y, K_z$ ;
```

```
//The tip selection process is optimized by considering  
transaction weights, cumulative weights, and node connectivity.
```

```
//The RA optimization ensures that nodes with higher  
computational resources or less load are prioritized during the tip  
selection process.
```

```
 $Cumulative\ Weight = \sum_{Z \Rightarrow x} W_Z + W_A$ ; //Using eqn.(4)
```

```
//Here the cumulative weight of a node x is calculated as the sum of the weights  
from all nodes z
```

```
 $P_{xy} = \exp(-\alpha(K_x - K_y)) \left( \sum_{Z \Rightarrow x} \exp(-\alpha(K_x - K_z)) \right)$ ; //Using eqn.(5)
```

```
// Then the separation probability  $P_{xy}$  for each step taken by the walker from the  
current node x to a potential next node y is calculated to select the transaction with  
higher cumulative weights
```

```
}
```

```
Verification ()
```

```
{
```

```
// after that, the verification process is performed by detecting conflicts to prevent  
double-spending, validating transaction fields, checking digital signatures using  
public key, and confirming the cumulative weight and consistency of references  
before adding transactions to the Tangle.
```

```
}
```

```
Security Analysis ()
```

```
{
```

```
//here analyze the overall security and trustworthiness of the tangle
```

```
}
```

```
Performance Validation ()
```

```
{
```

```
//estimating the performance
```

```
}
```

```
End
```

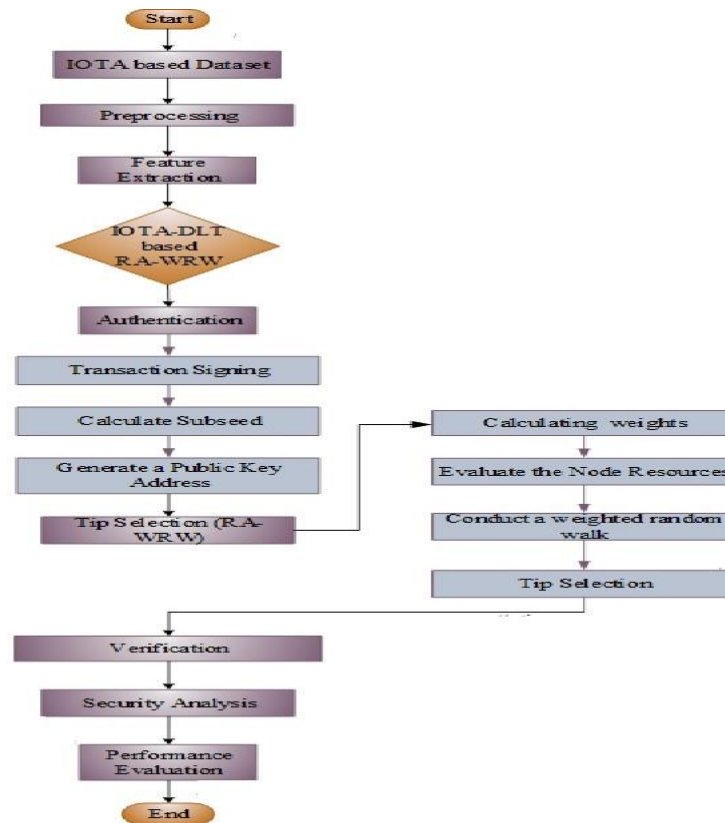


Figure 4: Flowchart of proposed IOTA-DLT-based RA-WRW

Figure.4. shows the flowchart for the IOTA-DLT-based RA-WRW, and algorithm.1. provides the tip selection process. After implementing the designed model, the results are estimated in terms of execution time, CPU usage, f-measure, recall, accuracy, and precision, Confirmation Time, and Time Complexity were computed.

5. Result and Discussion:

The latest study introduces a hybrid model designed to optimize the overall enhancement of the IOTA DLT network, aiming to elevate its scalability and performance. The IOTA-based dataset was collected from the standard (Kaggle) website and fed into the system. Hereafter, a novel IOTA-DLT-based RA-WRW has been designed with the required parameters to determine the execution time and CPU usage by improving confirmation time in tip selection. The designation and implementation descriptions are tabulated in Table 2.



Table 2. Parameter Description

Platform	PYTHON
Version	3.9.13
Processor	Intel(R) Core(TM) i5-3570 CPU @ 3.40GHz 3.40 GHz
Edition	Windows 10 Pro
System Type	64-bit operating system, x64-based processor
Installed RAM	8.00 GB (7.88 GB usable)
Version	22H2
Node resources	CPU, memory
Transaction weights	Based on the transaction amount and timestamp

5.1. Dataset Description

The Transaction dataset is taken from the Kaggle open-source website, it comprises several key attributes. 'User Id' stands as a distinctive identifier for each user, ensuring individualized tracking and analysis. 'Transaction Id' holds unique codes associated with each transaction, enabling precise transaction identification. 'Transaction Time' logs the specific timestamp of each transaction, providing a chronological perspective. 'Item Code' is dedicated to the unique code assigned to each purchased item, acting as a reference for the products acquired. 'Sender Address' contains a description of the product's sender, offering additional contextual information. 'Number of Items Purchased' indicates the quantity of each item bought in a given transaction. 'Cost per Item' denotes the unit price of each purchased item, facilitating financial assessments. Finally, 'Receiver Address' records the country where the item's recipient is located, providing insight into geographic trends and preferences. With these diverse attributes, this dataset enables a comprehensive analysis of user transactions, item details, and purchase behavior across different regions, while also offering insight into the sender's information. <https://www.kaggle.com/datasets/vipin20/transaction-data>



5.2 Performance metrics

To assess the effectiveness of our proposed RA-WRW model built on the IOTA-DLT framework, we gauge its performance through key metrics, namely accuracy, precision, recall, and f-measure.

5.2.1 Accuracy:

This description defines accuracy as the proportion of correctly confirmed nodes in the IOTA tangle among all participating nodes. Specifically, accuracy is characterized as the ratio of accurate positive to accurate negative findings necessary for the complete outputs of the proposed model. The model demonstrated superior accuracy compared to alternative methods currently in existence. The accuracy of Proposed IOTA-DLT-based RA-WRW method is graphically represented in below figure.5.

$$A^* = \frac{TPt^* + TNt^*}{TPt^* + TNt^* + FPt^* + FNt^*} \quad (6)$$

Where A^* represents accuracy, TPt^* signifies true positive, TNt^* denotes true negative, FPt^* stands for false positive, and FNt^* Indicates false negative.

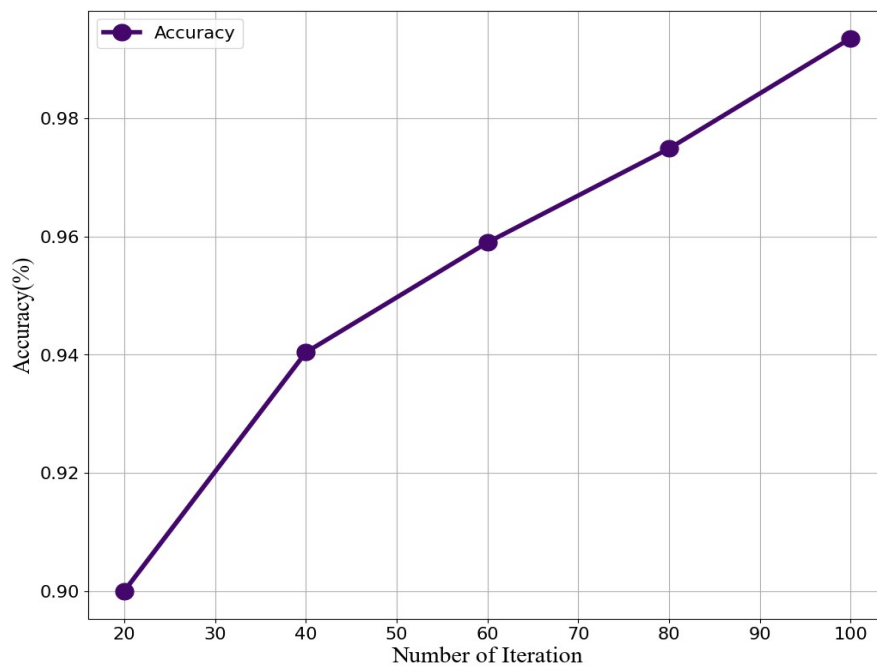


Figure 5. Accuracy of Proposed IOTA-DLT-based RA-WRW method



5.2.2 Precision:

Precision assesses the accuracy of a model's positive predictions by calculating the ratio of true positives to the total number of predicted positives. The proposed model achieved high precision when compared to other existing methods. The precision of Proposed IOTA-DLT-based RA-WRW method is graphically represented in below figure.6.

$$P^* = \frac{TPt^*}{TPt^* + FPt^*} \quad (7)$$

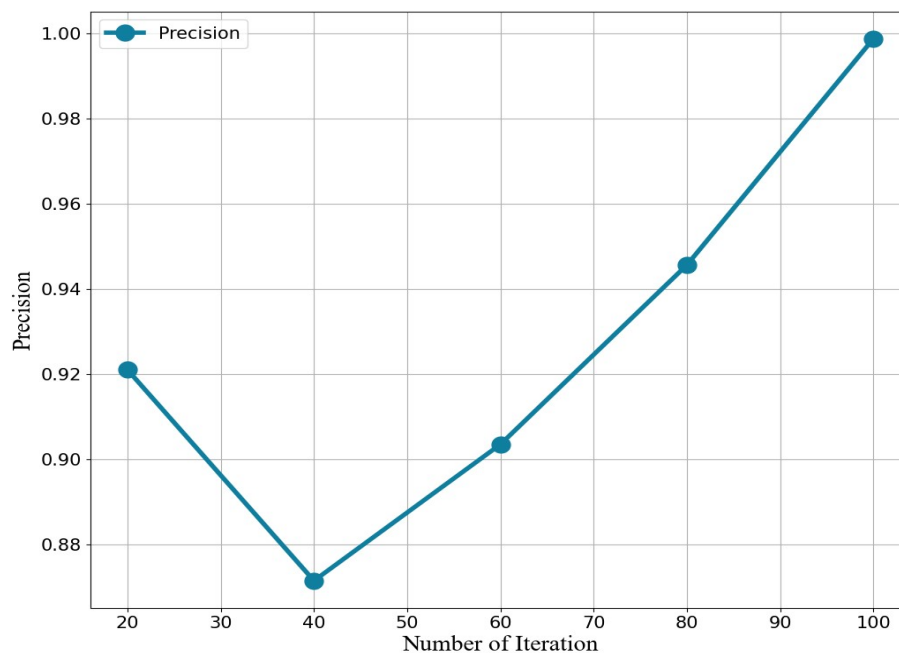


Figure 6. Precision of Proposed IOTA-DLT-based RA-WRW method

5.2.3 Recall:

Recall, expressed as a percentage, gauges the model's ability to correctly detect positive instances by dividing the number of true positives by the total count of actual positives. The proposed model achieved a high recall when compared to other existing methods. Recall of the Proposed IOTA-DLT-based RA-WRW method is graphically represented below in figure.7.

$$R^* = \frac{TPt^*}{TPt^* + FNt^*} \quad (8)$$

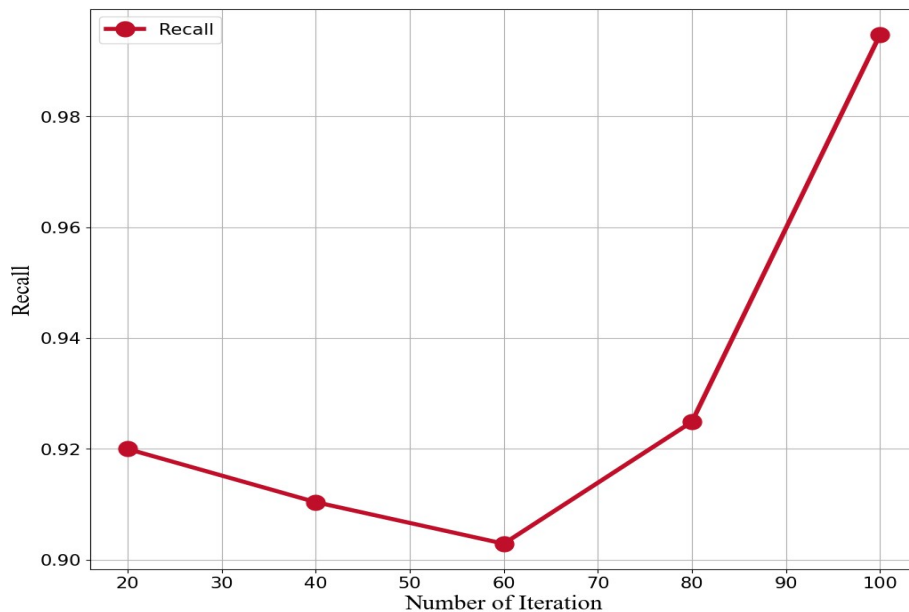


Figure 7. Recall of Proposed IOTA-DLT-based RA-WRW method

5.2.4 F-Measure:

The F-measure is a measure of the technique's accuracy on the considered dataset. It is the fraction of the suggested value's recall and precision values. The proposed model achieved a high f-measure when compared to other existing methods. F-Measure of Proposed IOTA-DLT based RA-WRW method is graphically represented in below figure.8. It is calculated using the following eqn.

$$F_v^* = \frac{P^*}{R^*} \quad (9)$$

Here, F_v^* indicates the f-measure P^* Represent precision, and R^* Signifies the recall.

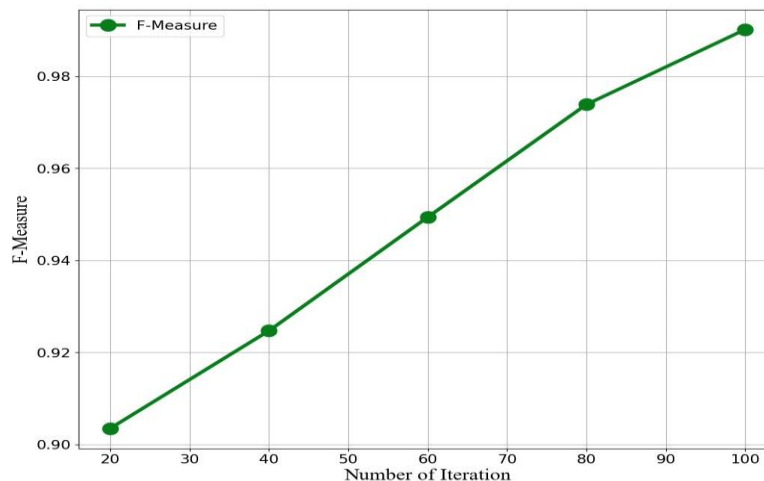


Figure.8. F-Measure of Proposed IOTA-DLT-based RA-WRW method

5.2.5 Time Complexity:

Time complexity measures the computational efficiency of an algorithm by evaluating the duration it takes to execute the input size. It characterizes the algorithm's runtime growth concerning the size of the input. By employing the proposed IOTA-DLT-based RA-WRW method, achieved a linear time complexity. Linear time complexity ($O(n)$) means that as input size increases, the algorithm's runtime grows proportionally. The Time Complexity of the Proposed IOTA-DLT-based RA-WRW method is graphically represented below in figure.9.

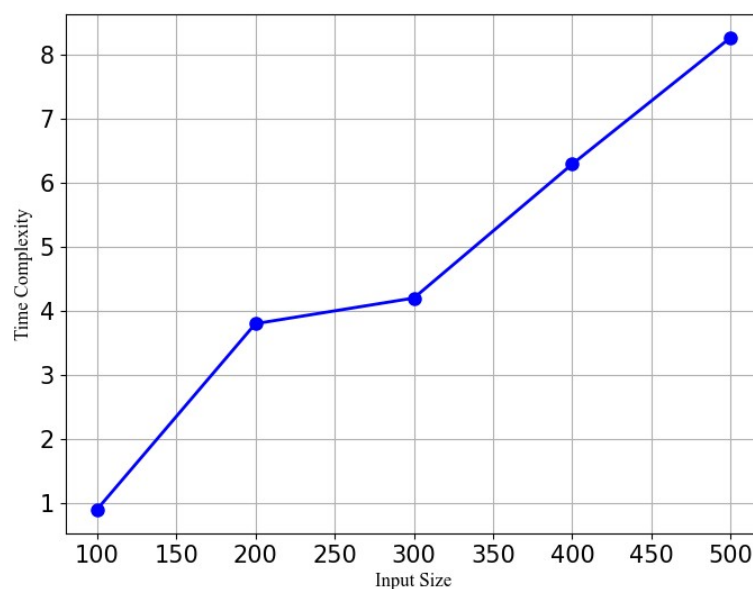


Figure 9. Time Complexity of Proposed IOTA-DLT-based RA-WRW method



5.2.6 Confirmation Time:

Confirmation time is the period required for a transaction to be verified and incorporated into the decentralized ledger or Tangle within the IOTA network. This model achieved a tip confirmation time of 4.5 seconds. The confirmation Time of the Proposed IOTA-DLT-based RA-WRW method is graphically represented below in Figure 10.

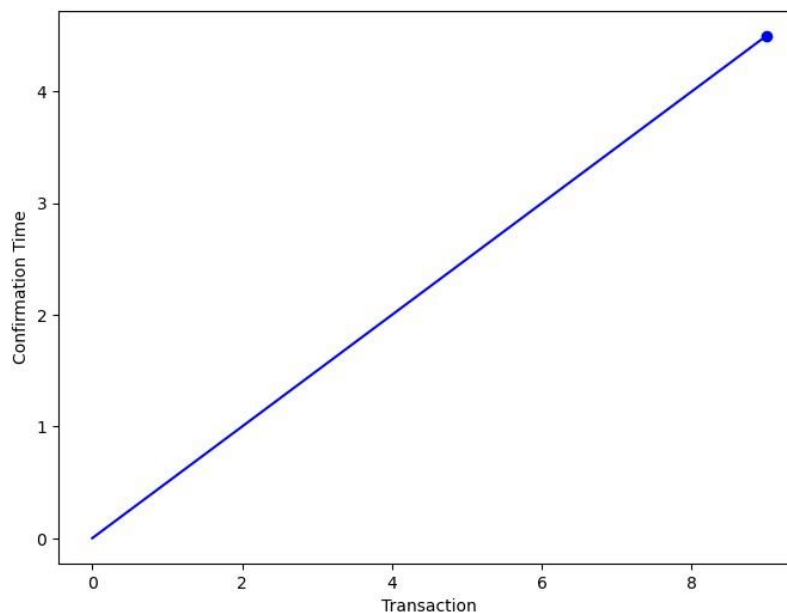


Figure 10. Confirmation time of Proposed IOTA-DLT-based RA-WRW method

5.2.7 Execution Time:

Execution time, or runtime, is the duration a program takes to complete its tasks on a computing system. It encompasses all processing steps from start to finish. The time it takes to execute a program can fluctuate depending on elements such as program complexity, algorithm efficiency, and input data size. It is a crucial metric in evaluating the performance and efficiency of software, especially in scenarios where processing speed is a critical factor. In this work, here it achieved a better execution time of 43.8 seconds. The execution time of the proposed IOTA-DLT-based RA-WRW method is graphically represented in the figure.11.

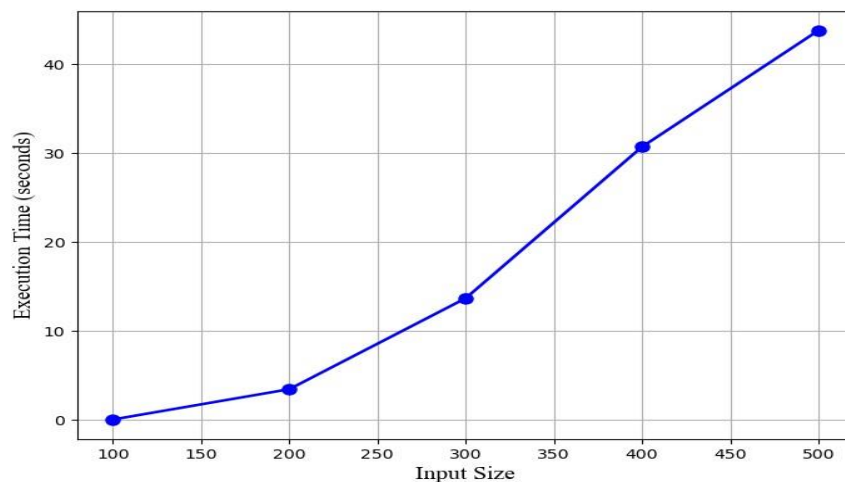


Figure 11. Execution time of proposed IOTA-DLT-based RA-WRW method

5.2.8 CPU Usage:

CPU usage is a component of resource usage that refers to the collective utilization of various system components, which can include the CPU, memory (RAM), disk storage, and network bandwidth. And also it refers to the proportion of a computer's processing power that is being utilized at any given time. It represents the amount of computational work the CPU is performing relative to its maximum capacity. By utilizing the proposed model achieved a CPU usage value of 22.9%. CPU usage of the proposed IOTA-DLT-based RA-WRW method is graphically represented in the given below Figure 12.

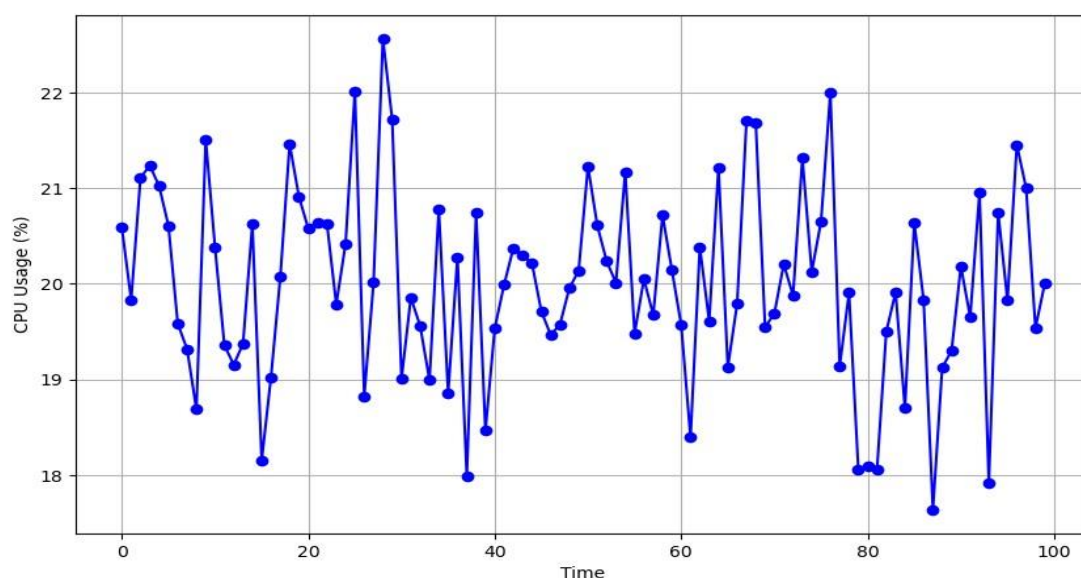


Figure.12. CPU usage of proposed IOTA-DLT based RA-WRW method



5.3. Comparative Analysis:

The model will be integrated into the Python framework, and its performance has been validated by assessing metrics such as accuracy, precision, recall, and f-measure. Additionally, a comparative analysis was conducted with other established models, including Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN) [30]. The comparison values of existing work is given in the below table.3.

Table 3. Comparison values of existing works

Techniques	Accuracy	Precision	Recall	F-Measure
CNN	85.7	86	85	86.44
GRU	86.6	87.5	84.4	86.5
RNN	85.55	87.6	87.6	85.5
LSTM	97.34	97	96.78	97.6
IOTA-DLT based RA-WRW (Pro)	99.35	99.19	99.36	99.28

5.3.1. Comparison between the suggested approaches and current methods regarding accuracy:

The results obtained were compared with various methods to assess their performance, primarily focusing on accuracy. The findings revealed that RNN achieved an accuracy level of 85.55%, which was notably lower than all other methods. Moving on to CNN, it exhibited a slightly better performance with an accuracy level of 85.7%, although it still lagged behind other approaches. In contrast, the GRU model displayed improved results with an accuracy level of 86.6%, surpassing both RNN and CNN. However, it remained inferior to the other methods under consideration. LSTM outperformed all previous models with an impressive accuracy level of 97.34%. Remarkably, the proposed method, IOTA-DLT based RA-WRW, achieved the highest accuracy score of 99.35%, surpassing all other methods in the comparison. The Comparison graph of accuracy is represented in below figure.13.

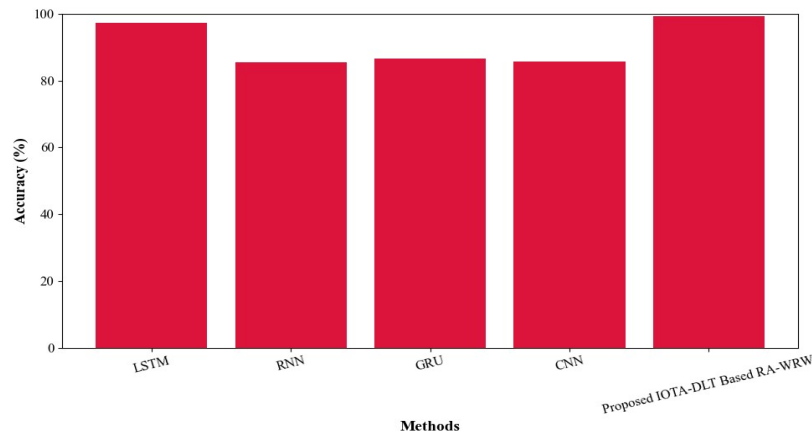


Figure 13. Comparison graph of Accuracy

5.3.2. Comparison between the suggested approaches and current methods regarding Precision:

When assessing precision, our proposed method, IOTA-DLT based RA-WRW, was compared to other methodologies. CNN exhibited a precision rate of 86%, which ranked comparatively lower than the other methods. Moving on to GRU, it achieved a precision value of 87.5%, surpassing CNN but still falling short of the remaining techniques. RNN followed closely with a precision score of 87.6%, outperforming CNN and GRU but trailing behind the other approaches. LSTM notably excelled in precision with a score of 97%, while DNN exhibited even higher precision at 99%. However, the IOTA-DLT based RA-WRW method outshone them all, securing an impressive precision score of 99.19%, indicating superior precision compared to the existing methods. The Comparison graph of precision is represented in below figure.14.

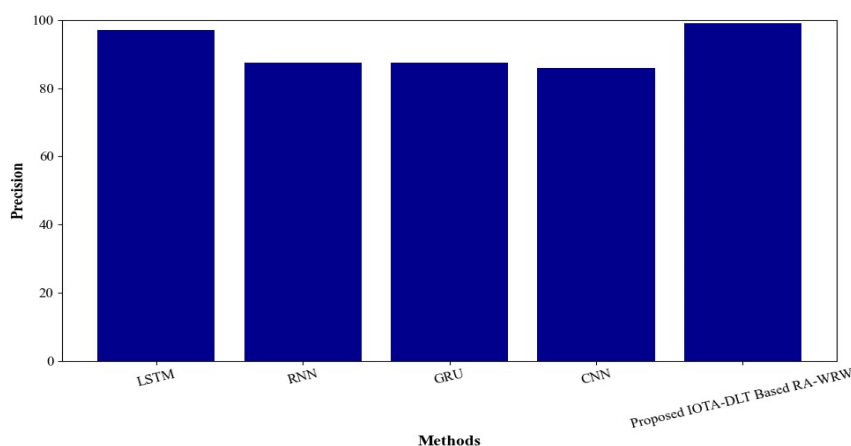


Figure 14. Comparison graph of Precision



5.3.3. Comparison between the suggested approaches and current methods regarding Recall:

In the evaluation of recall, our IOTA-DLT based RA-WRW method was compared to established approaches. Notably, GRU displayed the lowest recall value at 84.4%, falling behind all other methods. CNN, on the other hand, achieved a recall rate of 85%, surpassing GRU but still trailing behind the remaining techniques. RNN delivered a slightly improved recall score of 87.6%, outperforming both GRU and CNN, although it remained inferior to the other methods. LSTM emerged as a recall leader with a score of 96.78%. Remarkably, our proposed IOTA-DLT based RA-WRW method excelled in recall, scoring an impressive value of 99.36%. This result demonstrated superior recall compared to the existing methods. The Comparison graph of recall is represented in below figure.15.

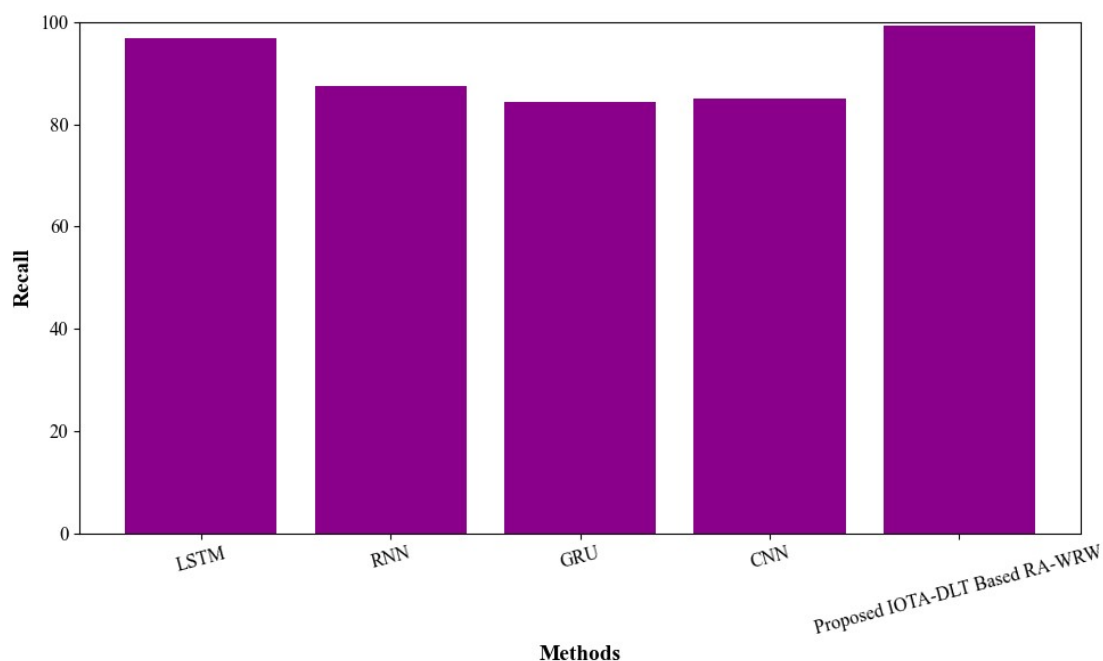


Figure 15. Comparison graph of Recall

5.3.4. Comparison of proposed with existing methods in terms of F-Measure:

In the assessment of F-Measure, our proposed method, IOTA-DLT based RA-WRW, was compared to various alternative approaches. RNN displayed the lowest F-Measure at 85.5%, positioning it at the lower end of the rankings. CNN, while performing better, achieved an F-Measure of 86.44%, surpassing RNN but still falling short of the remaining methods. GRU delivered an F-Measure score of 86.5%, showing improvement over both RNN and CNN, although it remained behind the other methods in the comparison. LSTM emerged as a strong



contender with an F-Measure of 97.6%. However, the IOTA-DLT based RA-WRW method demonstrated exceptional F-Measure results, achieving a score of 99.28%. This outcome highlighted its superior performance compared to the existing methods. The Comparison graph of F-Measure is represented in below figure.16.

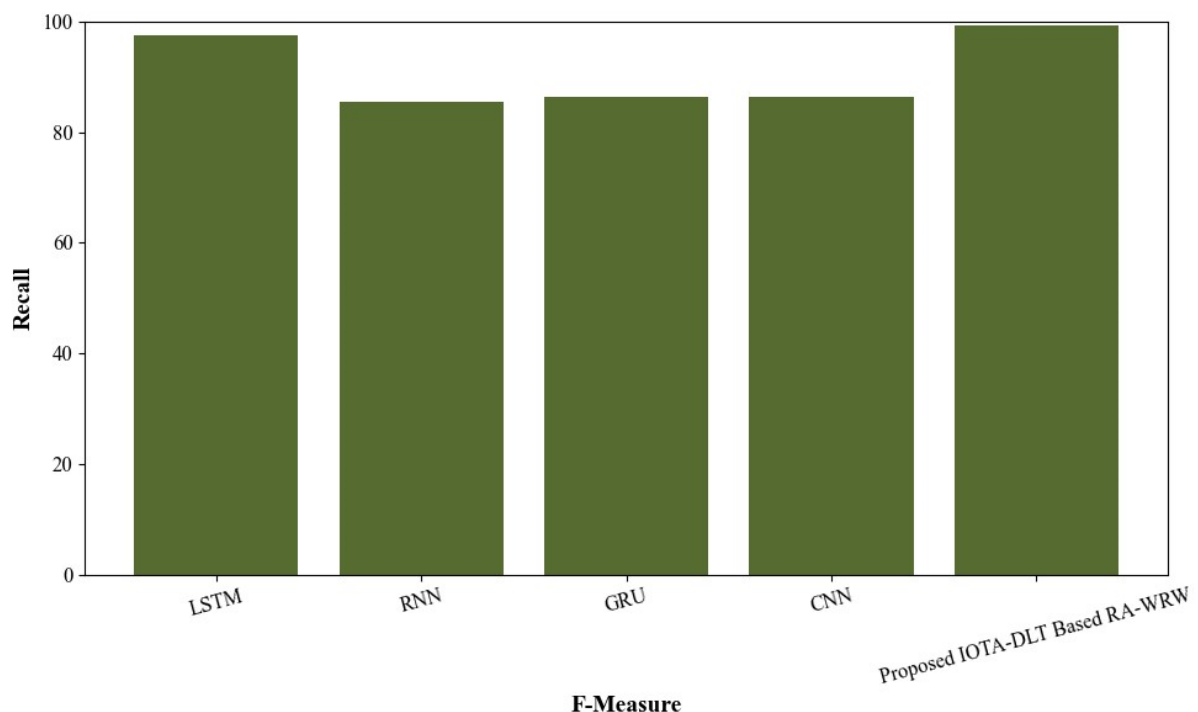


Figure 16. Comparison graph of F-Measure

5.4. Discussion on Societal Impact and Practical Applications

The proposed RA-WRW study on optimizing execution time and CPU usage in the IOTA network using DLT offers significant societal benefits. Optimizing CPU usage reduces the energy consumption of IoT devices, contributing to greener and more sustainable technology solutions. By enhancing the efficiency, scalability, and security of IoT systems, the research supports practical applications across industries such as smart cities, healthcare, and transportation, leading to improved performance and reduced operational costs. It advances related fields like DLT and resource allocation algorithms, the developed the RA-WRW algorithm presents new possibilities for optimizing computational resources, promoting better resource management and sustainable technology solutions. Additionally, the study addresses key societal challenges, including energy efficiency, environmental sustainability, economic growth, and improved public services, ultimately contributing to a higher quality of life and smarter management of resources.



6. CONCLUSION

In this work, presents a comprehensive approach to enhance IOTA network transaction efficiency. The IOTA-DLT-based RA-WRW algorithm represents a significant advancement in tip selection optimization. The authentication process using the sender's private key ensures tip integrity and verification procedures further affirm their authenticity. The security analysis demonstrates the resilience of the IOTA network against various attack vectors, highlighting the robustness of the approach. The novelty lies in integrating resource allocation with the weighted random walk strategy, offering a unique solution to distributed ledger transaction processing. Comparative analyses against existing methods confirm the superior performance of our model, boasting high accuracy, f-measure, recall, and precision rates of approximately 99.35%, 99.28%, 99.36%, and 99.19% respectively. This underscores the novel algorithm's efficacy in optimizing tip selection processes in the IOTA tangle.

Future research should expand the IOTA-DLT-based RA-WRW algorithm for IoT and supply chain applications, enhance security with advanced cryptography, improve scalability with adaptive algorithms, and integrate machine learning for transaction prediction and fraud detection. Additional efforts should focus on reducing energy consumption, ensuring DLT interoperability, improving user interfaces, maintaining regulatory compliance, setting performance benchmarks, and developing educational resources.

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