IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⯑ Peer-reviewed & Refereed journal ⯑ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13571

An Integrated Machine Learning and Blockchain Framework for E-Waste Forecasting and Traceability

Jaswanth Raj J[1], Kevin Dhyanesh V R[2], Krishna P[3], Dr. Maniraj S P[4]

Department of Computing Technologies, School of Computing,

SRM Institute of Science and Technology, Chennai, India[1,2,3]

Assistant Professor, Department of DSBS, SRM Institute of Science and Technology, Chennai, India[4]

Abstract: One gadget after another piles up worldwide, piling pressure on nature's limits - trash from old phones and laptops might hit 80 million tons by 2030. Behind the scenes, today's recycling networks struggle: they're run by too few hands, hard to track fully, open to cheating or altered logs. Tackling these two issues at once, a new system links smart forecasts with tamper-proof digital records. Numbers pulled from past trends between 2010 and 2023 feed into a math model; things like people count, money per person, online access help guess future waste amounts. From those patterns, predictions stretch ahead - from 2026 through 2030 - showing where trash tides may rise. One way to track old electronics uses Python, building a chain of records locked with SHA-256 math plus agreement through computing effort. Instead of paper logs, it runs on a live web interface made with Streamlit, storing data in MySQL. Tests show predictions stay close to real outcomes - over 96 percent match by one measure. This setup links smart forecasts to verified tracking, fitting global targets for responsible tech, cleaner production, and climate action.

Index Terms: E-Waste, machine learning, blockchain, linear regression, SHA-256, proof of work, forecasting, traceability, streamlit, sustainability.

I. INTRODUCTION

Stuff like old phones, computers, screens, and broken kitchen gadgets count as e waste once they stop being used. Not long ago, such items made up just a small part of trash piles worldwide - now their numbers grow faster than almost anything else we throw away. In 2019 alone, official records showed about 53.6 million metric tons spilling into landfills or scrapyards. Experts expect that number to climb past 80 million tons within ten years if trends hold. Even so, only a tiny fraction - less than twenty percent - ever reaches proper recycling sites where parts might be reused safely.

Heavy metals hide inside old electronics. When trash trucks roll toward dumps, circuit panels spill lead and mercury underground - water catches the poison first. Nearby homes drink what leaks through dirt. Gold vanishes too, buried under broken gadgets tossed aside without care. Copper wires burn in backyard fires, smoke carrying harm skyward. Rare earths disappear forever if nobody pulls them out before rot sets in.

Even though this issue is huge, today's electronic waste handling relies on broken frameworks. When data lives apart in isolated hubs, tampering becomes easier - fake recycling papers appear, overseas transfers slip under the radar, oversight lacks proof from start to finish. Prediction gaps also remain wide; without smart models ahead of time, building proper systems or shaping rules happens blindly.

A new kind of digital record system handles trust issues in a unique way. Because each piece of data is locked into place using math-based seals and spread across many computers, changing old entries without detection turns nearly impossible - any tampering shows up plainly down the line. At the same time, systems that learn from past trends can spot recurring behaviors in waste flows, then forecast future needs so teams adjust collection networks before demand spikes.

This study introduces a unified approach linking two methods to tackle prediction and tracking at once. What stands out here is how it handles both tasks together through one system

Starting with past patterns, a forecast tool learns from old electronics waste numbers between 2010 and 2023. Instead of guessing, it watches how income, population, and tech use shift year by year. Because habits change slowly, the system adjusts its expectations step by step. While trends evolve, the method sticks close to real-world behavior. Behind each estimate lies a trail of actual usage, not assumptions. Over time, small changes add up - so projections stretch forward carefully.

By 2030, what emerges reflects steady growth shaped by society's rhythm.

A fresh start each time shapes how this system runs - built with Python, it forms a unique chain where every step stays locked in place through SHA-256 codes. Instead of relying on third parties, work must be shown before anything gets

DOI: 10.17148/IARJSET.2026.13571

added, keeping records firm. From drop-off to final handling, movements of old electronics gain trust because changes need effort to prove they belong. Each piece fits only when the math checks out, making tampering stand out fast.

A single Streamlit interface brings together forecast tools with blockchain tracking, connected to a MySQL system through XAMPP. This setup links live predictions and transaction logs under one view, using secure chains for data flow. Behind it all, structured storage keeps information organized and accessible across modules.

One piece checks what shape gadgets are in, sorting them as good to reuse, fit for recycling, or ready for trash. It logs toxic stuff details every time it processes a unit.

What comes next breaks down like this. After that, Section II looks at earlier studies. Following this, Section III outlines missing pieces spotted during review. Right after, Section IV walks through the method suggested along with how the system is built. Then again, Section V covers what tech and tools were used. Lastly, Section VI shares findings together with their breakdown. Outcomes get tied to SDGs in Section VII. What comes next is the closing thoughts plus what might follow, then citations appear after that.

II. RELATED WORK

A lot of work has gone into using blockchains for handling old electronics. Khan and Ahmad [1] built a system on Ethereum meant for intelligent urban areas - it links internet-connected devices to automatic contract steps when ownership shifts. Even though every gadget can be followed from start to finish, there is no built-in prediction tool using learned data patterns.

Poongodi and team [2] introduced a system for handling electronic waste through blockchain smart contracts powered by 5G networks. While their approach lays out ideas clearly, real-world testing remains sparse. In another case, Farizi with Sari [3] developed a functional model using Hyperledger Fabric - showing how it runs in practice yet skipping any head-to-head analysis between open and controlled consensus setups.

Starting off differently, Dua and team [4] looked into rewards using tokens to support proper waste handling in 5G-linked local setups - yet they left out tracking recovered materials. Meanwhile, work by Dasaklis, Casino, and Patsakis [5] focused more sharply on checking returns processes, building a custody trail secured through blockchain; it showed solid proof for tracing backward flows even if future predictions weren't built in.

In 2023, Santhuja and Anbarasu [6] linked sensor-driven device tagging to a blockchain record, using IoT tools alongside distributed ledgers to trace gadgets - yet their model lacked detail when handling dangerous substances. Meanwhile, Sahoo, Mukherjee, and Halder [7] introduced a single blockchain framework aimed at worldwide e-waste control, emphasizing oversight in its design; however, real-world testing stayed minimal.Back in 2024, Ambre along with Trivedi looked at how tough it can be putting a controlled blockchain system into place for handling trash within smaller companies - real-world steps were shared, yet predictions or long-term load estimates stayed out of view. Meanwhile, stepping away from blockchains entirely, Forti and team delivered the core data behind the Global E-Waste Monitor, showing worldwide patterns though leaving out any setup for tracking items digitally.

III. RESEARCH GAPS IDENTIFIED

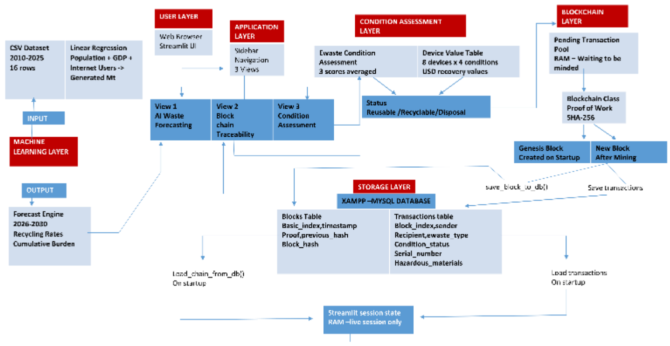
Looking at what's already been studied, these key missing pieces stand out:ased on the review of existing literature, the following critical research gaps are identified:

1. Most systems miss linking smart predictions with secure digital tracking for old electronics. One piece guesses what happens next using data patterns. Another logs device history on a shared ledger. These two rarely work together. Split functions mean delays, mismatched records. A combined setup could align foresight and transparency. Gaps remain when they stay apart. Matching both might improve accuracy across the chain. Right now, that bridge does not exist.
2. Nothing builds up when old loads aren't carried forward, especially if every move is logged online. Tracking each exchange digitally keeps tabs without stacking leftover weight behind the scenes.
3. No quantitative forecasting accuracy validation in blockchain-based e-waste systems.
4. Limited material recovery accounting integrated per blockchain transaction.
5. Not enough contrast exists when looking at public versus controlled consensus methods for handling electronic waste tasks.
6. Most testing happens in labs, not cities, so officials rarely see how it works out there. Real streets would show what truly breaks or holds up under daily chaos.
7. Most basic IoT gadgets lack strong ways to verify identity or resist tampering right now.

DOI: 10.17148/IARJSET.2026.13571

8. Starting with gap number one, the system uses machine learning predictions tied to blockchain tracking. Instead of skipping ahead, it includes detailed data on dangerous substances. Moving forward, total accumulated impact gets estimated step by step. By the end, how well forecasts match real results is checked using R squared values.

IV. PROPOSED METHODOLOGY



A. Data Collection and Preparation

From 2010 up through 2023, information on worldwide electronic waste was gathered, forming a clear set of 16 entries. This collection includes specific factors tied to society and economy that influence how much e-waste is produced

Each year tracks how many people live on Earth altogether.

One way to measure how much a country produces? Look at its GDP
- total value of goods and services, shown in trillions of U.S. dollars. This number hints at overall economic movement , tied closely to what people and businesses use. Think of it as a snapshot of spending and output combined, but counted in dollar terms across a full year.

Most people on Earth now use the web through phones or computers. That number shows how widely tech has spread across countries.
Access varies, yet connections keep growing each year. Devices link homes, schools, and workplaces in many regions. Some areas still lack stable service, though progress continues. Connectivity shapes communication, learning, jobs, da ily routines.

• E-Waste Generated (Mt): The target variable representing total e-waste in million metric tonnes.

Features got normalized first, after that missing values were taken care of. The structure was then shaped into a format ready for training a regression model using scikit-learn.

B. Machine Learning Forecasting

At the heart of forecasting electronic waste lies a basic equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

Where:

- y= Predicted E-Waste (target variable)
- β_0= Intercept
- $\beta_1, \beta_2, \beta_3$= Coefficients (learned by model)
- x_1= Population
- x_2= GDP
- x_3= Internet Users

Out of Python's scikit-learn tools came a linear regression setup. Population, GDP, alongside Internet Users shaped the inputs; E-Waste Generated stood as the outcome measured. Training used most of the data - eighty percent - leaving twenty for testing. This split guided how the model learned patterns before checking its guesses.

International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 5, May 2026
DOI: 10.17148/IARJSET.2026.13571

Performance of your model gets measured using this formula:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Where:

- y_i= Actual value
- $\hat{y}_i$= Predicted value
- $\bar{y}$= Mean of actual values

Out of nowhere, R^2 stepped in to measure how well the three selected factors explained differences in e-waste amounts. Following that, the completed model shifted toward predicting what might happen next, sketching out possible social and economic paths ahead. Because of this setup, forecasts for e-waste emerged covering 2026 to 2030. Hidden within those numbers were splits - recycled portions stood apart from what went unprocessed. On top of that, a running total built up, showing long-term accumulation left in nature.

C. Blockchain-Based Traceability Implementation

1. Hash Function Using SHA256
2. Find p prime so hash of p and p prime begins with four zeros
3. Block Hash Equals SHA256 of Block
4. Chain Linking Block i plus one previous hash equals hash of block i
5. Chain validity requires matching prior block hash and met proof criteria

A unique blockchain system built with Python started logging e-waste movements among participants. Inside every linked block sits data about each exchange: who sent it, when it moved, what type of device, its weight, destination, and verification timestamp. One person sends it. Another gets it. Each has a name. Or maybe just a code. Names show who is involved. Codes do too. Either works fine here. People need labels. So does data flow.

What kind of electronic waste you have along with the unique ID code on the machine. • Device condition (Reusable / Recyclable / Disposal). • Hazardous materials associated with the device. Every record holds a moment in time plus its place within the chain. Location inside the sequence ties to when it was made.

It starts with a Genesis Block when the system turns on, each one built upon the last by holding its SHA-256 fingerprint inside. Change an old entry? Everything after breaks without delay. To join the chain, a block must meet a tough condition - its hash needs several zero digits at the front - achieved through Proof-of-Work. New records come in as freshly mined units linked one after another. Inside the system, information sticks around using a MySQL setup through XAMPP - so it shows up again later. Waiting to be processed, deals sit in a temporary space held in memory while things run.

D. Device Condition Assessment Module

One part checks old electronics by rating them on three things, then averaging those numbers into one overall mark. Depending on that number, each gadget gets sorted into reusable, recyclable, or trash. Eight kinds of items - like phones, computers, watches, ovens - are placed into four quality grades. Each combo has a dollar amount tied to it, showing how much value comes back when materials are recovered. The system adds up financial returns during every exchange using these fixed rates.

E. System Architecture

The system follows a three-layer architecture:

Web interface runs on Streamlit, offering three key sections: AI Waste Forecasting, Blockchain Traceability, after that, Condition Assessment. People navigate through a sidebar using any standard browser. While the layout stays consistent, each view serves a distinct function without overlap.

Python runs the backend smarts. It manages predictions using Linear Regression. Block creation and checks on the chain happen here too. Condition scores get calculated in this layer as well. App_Production.py ties everything together. Three views come alive through that single file.

When the app starts up, it pulls the blockchain data and transaction records from a MySQL database running on XAMPP. This setup holds two main tables: one tracks blocks using fields like index, time stamp, proof value, prior hash, and current block hash. The second table logs transaction details such as which block they belong to, who sent them, who

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13571

received them, what kind of electronic waste is involved, its state, approval level, ID number, and whether dangerous substances are present. Instead of keeping everything in memory, the system reads stored entries at launch and places them into active session storage. Because of this, past activity remains accessible during use without repeated queries. Each piece loads just once when initializing. That way, interaction stays responsive while relying on persistent backend storage.

V. TOOLS AND TECHNOLOGIES

One piece made it work - then came another. A setup took shape around each part. Each bit fit where it needed to go. What held everything together showed up last

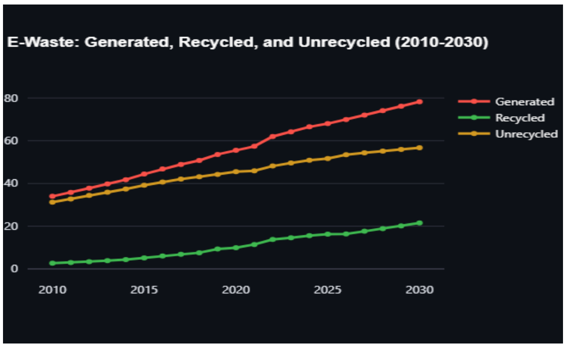
1. Python 3.x
2. Machine Learning with scikit-learn Linear Regression Pandas NumPy
3. Blockchain Built With Python Using SHA 256 And Proof Of Work
4. Frontend Dashboard Built with Streamlit
5. MySQL database using XAMPP
6. Development Environment Visual Studio Code
7. Git version control

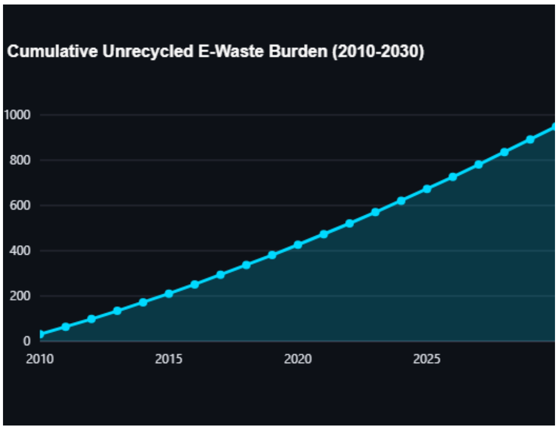
VI. RESULTS AND DISCUSSION

A. Machine Learning Forecasting Results

Out past the 0.96 mark went the R^2 score, showing how tightly the numbers followed what we picked - things like income shifts and web access trends. Instead of drifting apart, the pattern stayed close, linking bigger economies, more online users, then rising waste from electronics.

After 2026, electronic trash keeps climbing each year. By 2030, it could reach between 75 and 82 million metric tonnes worldwide if economies grow steadily alongside wider internet access. Recycling won't catch up - less than one out of four items will be processed during that time. Years of neglect pile up into massive amounts left untreated, calling for earlier planning and stronger systems now.





DOI: 10.17148/IARJSET.2026.13571

B. Blockchain Traceability Results

Every block made it into the chain with full verification, holding details of e-waste trades. Changing any old record would break every newer one - thanks to SHA-256 math puzzles securing each link. First up, a starting block fired to life when the system launched, setting the stage. After that, new blocks stacked neatly behind it, their creation growing tougher by design over time. After each session, the blockchain data stayed safe inside MySQL's built-in storage system. Every sequence of transactions was checked; none showed broken links or altered hashes. That outcome proved the record could not be changed without detection.

C. Device Condition Assessment

One step at a time, the system sorted each test gadget into its proper group using overall health points. Instead of guessing, it pulled exact reuse numbers straight from the Device Value Table across all eight types. Every sale now logs what materials can be reclaimed, no exceptions. What changed? A missing piece from past studies - tying reused resources directly to individual blockchain deals - is finally included.

D. System Dashboard

A live display built with Streamlit held everything together through three working sections. Inside the first section, predictions about waste appeared beside past patterns using clickable graphs. Moving to the next panel, people recorded electronic trash events, started block creation, then reviewed every linked entry. Last of all came checks on gadget status, showing how much they might return plus alerts if dangerous parts were found.

VII. SDG ALIGNMENT

Three UN Sustainable Development Goal are served by the outcomes of this work:

•SDG 12 — Because forecasts guide production, waste drops when plans match real demand. Tamper-proof logs show every step of a product's life. When records can't be faked, hiding bad disposal gets risky. Clear histories help builders shape reuse loops that actually work. Planning ahead pairs well with honest tracking. Systems start closing the loop once secrets vanish. Truth in data feeds better recycling paths.

• SDG 9 — Out here, upgrading trash systems means mixing smart software with secure digital records. A step forward happens when machines learn patterns while tracking garbage routes gets sharper. Old ways fade once tech helps sort what we toss more efficiently. Progress shows up where factories plug into networks that never forget a detail. Tools adapt as cities begin handling refuse like data flows. New life enters roads and bins whenever code runs quietly behind scenes. Watch how robots tag items while ledgers log every move underground.

• SDG 13 — Waste piles grow faster than most expect. When systems predict where trash will stack up next, cities adjust before problems spread. A record that cannot be altered keeps track of every disposal step. This stops secret dumping because someone is always watching. Trouble spots get flagged early now. Seeing what comes helps avoid what breaks. Proof stays locked in place so lies fall apart.

VIII. CONCLUSION AND FUTURE SCOPE

This paper proposes a system mixing machine learning with blockchain to track and predict old electronics waste. Using past worldwide numbers about discarded devices, a straight-line prediction method learned patterns fairly well. Two hundred fifty six hash marks show effort proof steps locked each record into place. Each step made sure information stayed visible and could never change afterward. Details like dangerous parts inside gadgets appeared alongside how much recycling might earn. One screen pulled everything together using live-updating tools anyone can view easily. Putting forecasts beside transaction logs created something real people could actually start using right away. Handling electronic trash got simpler because both pieces worked as one complete setup.

Starting fresh, it fills holes found in past studies - like how machine learning and blockchain rarely work together. One gap was missing models for dangerous substances. Another issue? Forecasting tools in tracking systems never got proper number checks. Instead of combining everything at once, earlier efforts left pieces untested.

Future work will explore the following directions:

Out here, live IoT feeds tag devices on their own, then shoot fresh details straight into the chain. Updates pop through without waiting when sensors recognize gear as it comes online. The system keeps moving - no pauses - each piece links up mid-action, feeding current bits right where they're needed.

Out front, machine learning tools like Random Forest help spot patterns over time. Behind the scenes, ARIMA adjusts for shifts that happen in sequences. Not far off, LSTM captures long-term dependencies others might miss. Tucked in between, blended approaches pull strength from multiple techniques. Each method brings something different to how future trends are shaped.

International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 5, May 2026
DOI: 10.17148/IARJSET.2026.13571

Putting systems live across cities or entire countries using massive real-world data, while checking they meet official rules and get approval from authorities who oversee regulations.

One piece fits into place when carbon checks join the system, then routing tweaks follow behind. A second layer shows up through smarter trash paths shaped by live data flow. Each step ties back to cuts in emissions tracked closely along the way. Routing shifts happen only after feedback loops confirm lower impact moves.

One way to test blockchains uses Proof-of-Stake instead of older methods. Another option checks how fast Hyperledger Fabric handles e-waste data when access is limited. Speed results come from running real-world trash tracking tasks. Each system processes records differently under the same load. Performance shifts based on design choices inside the network.

REFERENCES

[1] A. U. R. Khan and R. W. Ahmad, "A Blockchain-Based IoT-Enabled E-Waste Tracking and Tracing System for Smart Cities," IEEE Access, 2022.

[2] M. Poongodi, M. Hamdi, V. Vijayakumar, B. S. Rawal, and M. Maode, "An Effective Electronic Waste Management Solution Based on Blockchain Smart Contract," IEEE 3rd 5G World Forum (5GWF), 2020.

[3] T. S. Farizi and R. F. Sari, "Implementation of Blockchain-Based Electronic Waste Management System with Hyperledger Fabric," 2021.

[4] A. Dua, A. Dutta, N. Zaman, and N. Kumar, "Blockchain-Based E-Waste Management in 5G Smart Communities," IEEE INFOCOM Workshops, 2020.

[5] T. K. Dasaklis, F. Casino, and C. Patsakis, "Traceability and Auditing Framework for Electronic Equipment Reverse Logistics Based on Blockchain," 2020.

[6] P. Santhuja and V. Anbarasu, "Blockchain-Enabled IoT Solution for E-Waste Management," 2023.

[7] S. Sahoo, A. Mukherjee, and R. Halder, "A Unified Blockchain-Based Platform for Global E-Waste Management," 2021.

[8] D. Ambre and P. Trivedi, "Hyperledger Fabric-Based E-Waste Management System for Small-Scale Businesses," 2024.

[9] D. Kholiya et al., "Intelligent Framework for Waste Management Using Blockchain," 2023.

[10] D. Choudhary et al., "Blockchain-Enabled Architecture for Lead-Acid Battery Circularity," 2024.

[11] V. Forti, C. P. Balde, R. Kuehr, and G. Bel, The Global E-Waste Monitor 2020, 2020.

[12] A. K. Awasthi, X. Zeng, and J. Li, "E-Waste Management in India: A Review," 2019.

[13] K. Parajuly and H. Wenzel, "Potential for Circular Economy in E-Waste Management," 2017.

[14] K. Govindan, H. Soleimani, and D. Kannan, "Reverse Logistics and Closed-Loop Supply Chain: A Review to Explore E-Waste Management," 2018.

[15] S. Herat and P. Agamuthu, "E-Waste: A Problem or an Opportunity? Review of Issues, Challenges and Solutions in Developing Countries," 2016.

