

## Ai Enhanced E Tongue for Rapid Dravya Detection and Analysis

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### Abstract:

The AI-Enhanced Electronic Tongue (E-Tongue) is an emerging device that quickly and precisely identifies and analyses Dravya through a fusion of artificial intelligence and sensor technology. It replicates the sense of taste by an array of chemical sensors that react differently to various compounds. As a sample is introduced, they generate different electrical signals that correspond to the chemical nature of the substance.

These signals are processed and analysed through machine learning techniques like neural networks and pattern models. The AI module assists in recognizing, categorizing, and predicting the properties of different substances with high accuracy. This allows the system to perform fast dravya detection with guaranteed results without requiring sophisticated lab procedures.

The project involves developing an affordable, handheld, and intelligent analytical instrument appropriate for use in food quality testing, pharmaceuticals, Ayurvedic material authentication, and environmental monitoring. Through the use of AI, the E-Tongue learns from data constantly and enhances its detection capability with time. This technology is a significant leap in smart sensing technologies, providing quicker, more intelligent, and more efficient solutions for real-world substance analysis.

**KEYWORDS: E-Tongue, Dravya Detection, Artificial Intelligence, Machine Learning, Sensor Technology, Pattern Recognition.**

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### I. INTRODUCTION

Ayurveda, herbal medicine, nutraceuticals, and food systems all use dravya, and the increasing demand for quick, accurate, and scientifically validated techniques to identify and assess it is what spurred the development of an AI-Enhanced Electronic Tongue (E-Tongue) for Rapid Dravya Detection and Analysis. Conventional dravya authentication techniques mainly depend on expert experience, human sensory evaluation, or drawn-out laboratory processes. Despite their value, these methods are subject to subjectivity, inconsistency, lengthy analysis times, and high operating costs.

The frequency of adulteration, substitution, and quality variability, which have a direct impact on product safety and efficacy, are among the main

issues facing the modern herbal and natural product industries. Manufacturers may suffer financial losses, diminished therapeutic value, and serious health risks as a result of contaminated dravya. A scientific, automated, and quick quality assurance tool that can accurately differentiate genuine ingredients from inferior or tampered ones is desperately needed by the food and pharmaceutical industries.

Thus, the combination of AI and E-tongue technology marks a significant advancement in technology. High-precision dravya classification, intelligent calibration, adaptation to various environments, and automated learning of intricate chemical patterns are all made possible by it. This opens up new possibilities for the development of a portable, inexpensive, quick, and extremely accurate

system that can be used in real-world settings like food safety monitoring, agricultural quality grading, quality control labs, and Ayurvedic medicine standardisation. Furthermore, there is a growing need for scientific instruments that can validate dravya and facilitate regulatory standardisation as interest in natural medicines and traditional healing systems continues to rise globally. Ancient knowledge systems and contemporary analytical technology can be reconciled with an AI-enhanced E-tongue. Additionally, it creates new research opportunities in the fields of computational tasting, multi-sensor fusion, biomimetic sensing, and intelligent chemical diagnostics.

## II. LITERATURE REVIEW

An analytical sensing system called the Electronic Tongue was created to recognise substances by their chemical signatures related to taste. In order to create identifiable taste fingerprints, it uses arrays of non-specific sensors that react to dissolved compounds and produce unique signal patterns for every sample. These patterns are then processed using chemometric and statistical techniques. Compared to human sensory evaluation, this technology provides quick, objective, and repeatable results, which has led to its widespread use in food quality assessment, beverage classification, meat authentication, and adulteration detection. To guarantee consistent and dependable performance, high accuracy necessitates appropriate calibration and regulated sample conditions.

By simulating human taste perception through the five basic tastes, the project Electronic Tongues for Objective Taste Evaluation aims to create sensor based system that can distinguish and measure tastes in foods and beverages. The technology works by identifying chemicals that are related to taste and turning them into quantifiable signals that can be analysed. However, the primary disadvantages of this method are difficulties in adapting the sensors to the diverse and ever-changing food compositions found in the real world, as well as limited selectivity and sensitivity when working with complex mixtures [1].

In order to assess food quality more accurately than with conventional techniques, the project Applications of Electronic Nose (E-nose) and Electronic Tongue (E-tongue) in Food Quality Related Properties Determination investigates the use of sensor-based systems that replicate human taste and smell. When paired with sophisticated pattern recognition algorithms such as ANN, CNN, PCA, PLS, and SVM, these technologies offer quick, affordable, and precise evaluations for both in-line and off-line food monitoring. To guarantee dependable and consistent

results, their main disadvantage is the requirement for stringent control over sample preparation, sampling conditions, and data processing [2]. In order to precisely identify antioxidants such as BHA, BHT, and PG in olive oils, the project Development of a Voltammetric Electronic Tongue for the Simultaneous Determination of Synthetic Antioxidants in Edible Olive Oils combines chemometric instruments with a multisensor electrochemical system. The study used data fusion and pattern recognition techniques to obtain accurate and dependable results using square wave voltammetry with platinum and carbon fibre electrodes. The intricacy of data processing and calibration, however, is a disadvantage that might restrict its usefulness for regular or extensive quality analysis[3].

According to the project Historical Evolution and Food Control Achievements of Near Infrared Spectroscopy, Electronic Nose, and Electronic Tongue—Critical Overview, advanced sensing technologies such as NIR spectroscopy, E-nose, and E-tongue have been developed and are used to ensure food safety and quality throughout the production chain. When combined with chemometric tools, these instruments allow for the quick, economical, and accurate detection of adulteration and evaluation of food qualities. Their primary flaw, though, is their extreme sensitivity to environmental changes, which can compromise measurement accuracy even with the use of mathematical correction techniques[4].

Using a hybrid electronic tongue system with several electrochemical and optical sensors, the project Application of an E-Tongue to the Analysis of Monovarietal and Blends of White Wines aims to categorise and assess white wines according to grape variety and place of origin. The system successfully described wine samples and measured important quality parameters by utilising chemometric tools such as PCA, SIMCA, and PLS. The primary disadvantage, though, is that complex wine compositions may cause variations in sensor calibration and sensitivity, necessitating regular recalibration and data validation to ensure consistent accuracy[5]. In order to improve analytical performance, the project Multi- Transduction Sensing Films for Electronic Tongue Applications investigates the use of porphyrin-based sensing films that combine optical and electrochemical transduction techniques. The system increases detection sensitivity and accuracy by integrating information from electrochemical measurements and Computer Screen Photoassisted Technology (CSPT). The primary disadvantage, though, is the increased complexity of signal processing and data integration,

which may restrict scalability and realtime applications[6].

The goal of the Multi-transduction Sensing Films for Electronic Tongue Applications project is to improve the analytical performance of Electronic Tongue systems by combining the optical (CSPT-based) and electrochemical responses from porphyrin-based sensing films. The system enhances chemical discrimination and detection accuracy by simultaneously recording amperometric or potentiometric signals and capturing colour changes via a webcam and computer screen. However, because changes in lighting, humidity, or electrode response can impact reproducibility and reliability, it needs to be carefully calibrated and measured under stable conditions[7]. The development of artificial tongues into quick and affordable analytical instruments that can produce thorough sample fingerprints is covered in the chapter

#### Chemometric Brains for Artificial Tongues.

It draws attention to how chemometric methods can be used to process nonspecific sensor data and derive useful patterns for tasks involving recognition and classification. The method may encounter difficulties, though, such as difficult data interpretation and the requirement for cautious model selection to prevent mistakes and overfitting [8].

Using potentiometric E-tongue data, the study Comparison of Random Forest, Support Vector Machine, and Back Propagation Neural Network for Electronic Tongue Data Classification assesses three machine learning models for identifying various orange beverage and Chinese vinegar brands. The Random Forest classifier outperformed SVM and BPNN in terms of accuracy, indicating that it can handle small, multiclass, and unbalanced datasets with minimal preprocessing. However, when used on larger datasets, the approach might need more computational power and careful adjustment to prevent overfitting and complexity[9]. Using an electronic tongue system to categorise honey according to its floral and geographic origins is the main goal of the study Technique Potential for Classification of Honey by Electronic Tongue. The system effectively differentiated between various floral honey types using pattern recognition techniques like PCA, CA, and ANN. ANN also offered high accuracy (up to 95%) for classifying Acacia honeys from various regions. However, some floral origins overlapped in the PCA results, suggesting that careful modelling and sophisticated feature extraction may be needed to achieve consistent differentiation across all sample categories[10]. The E-Nose and E-Tongue Combination for Improved Recognition of Fruit Juice Samples project investigates a multisensor data fusion method that combines taste data from an

electronic tongue with aroma data from an electronic nose to more precisely classify commercial fruit juices. Fuzzy ARTMAP neural networks and low-level data fusion were used in the combined system, which produced a noticeably higher recognition accuracy than either device alone. However, this method necessitates more intricate sensor coordination and data processing, which could raise system costs and make calibration more challenging[11]. Methods for measuring perceived umami intensity across different food groups are examined in the study Quantification of Umami Intensity Using Sensory Evaluation, Chemical Analysis, and Electronic Tongue. The study showed that EUC and E-tongue-based predictions can accurately quantify umami in a variety of food categories by comparing sensory testing, equivalent umami concentration (EUC), and E-tongue data modelled using back propagation neural networks. Nevertheless, the method might have drawbacks when used for foods with intricate flavour matrices, necessitating calibration specific to each category and adding time and modelling effort[12].

Exploring the Relationships Between Perceived Umami Intensity, Umami Components, and Electronic Tongue Responses in Food Matrices is a project that uses neural network modelling, chemical analysis (EUC), and sensory evaluation to quantify umami taste across various food categories. The study shows that back propagation neural networks in conjunction with electronic tongue responses can reliably predict umami intensity, providing an unbiased substitute for human taste panels. The developed models, however, are category-specific, which means they might require recalibration and might not function reliably across complex or mixed food types[13]. Detection of Adulteration in Cherry Tomato Juices

The use of a combination of e-nose and e-tongue sensing systems to detect varying degrees of adulteration in tomato juice is examined in Based on Electronic Nose and Tongue. The study demonstrates that combining data fusion techniques with regression and classification models yields higher accuracy than using either tool alone[14].

By connecting sensor responses with meat quality parameters like pH, texture, and waterholding capacity, the project Electronic Tongue as a Correlative Technique for Modelling Cattle Meat Quality and Classification of Breeds shows how to use an electronic tongue system to distinguish beef from different cattle breeds. The study demonstrated that the e-tongue achieved high recognition and prediction performance, and that PCA and LDA analysis enabled accurate breed classification. However, the accuracy of breed classification may differ depending on the cuts or processing conditions

of the meat, and the system relies on meticulous sample preparation and calibration[15].

### III. METHODOLOGY AND SYSTEM ARCHITECTURE

#### 3.1 Overview

The AI-enhanced Electronic Tongue (E-Tongue) system for quick dravya detection and analysis was designed, developed, trained, and validated using a methodical approach that is described in the methodology. The entire process is described in this chapter, including sample preparation, sensor signal acquisition, preprocessing, machine learning model development, system integration, and experimental validation. Presenting a transparent, reproducible, and scientifically sound

procedure that guarantees the precision and resilience of the finished system is the aim.

#### 3.2 Overview of the System Architecture

The suggested approach has a modular design that includes:

Module for Sample Preparation:

- 1.E-Tongue Hardware Unit Sensor Array
- 2.System for Signal Acquisition and Calibration
- 3.Pipeline for Feature Engineering and Data Preprocessing
- 4.Development of AI and Machine Learning Models
- 5.Integration of the User Interface and Deployment
- 6.Verification and Assessment of Performance

Using an AI-enhanced E-Tongue, each module is made to guarantee the accuracy, consistency, and dependability of dravya analysis.

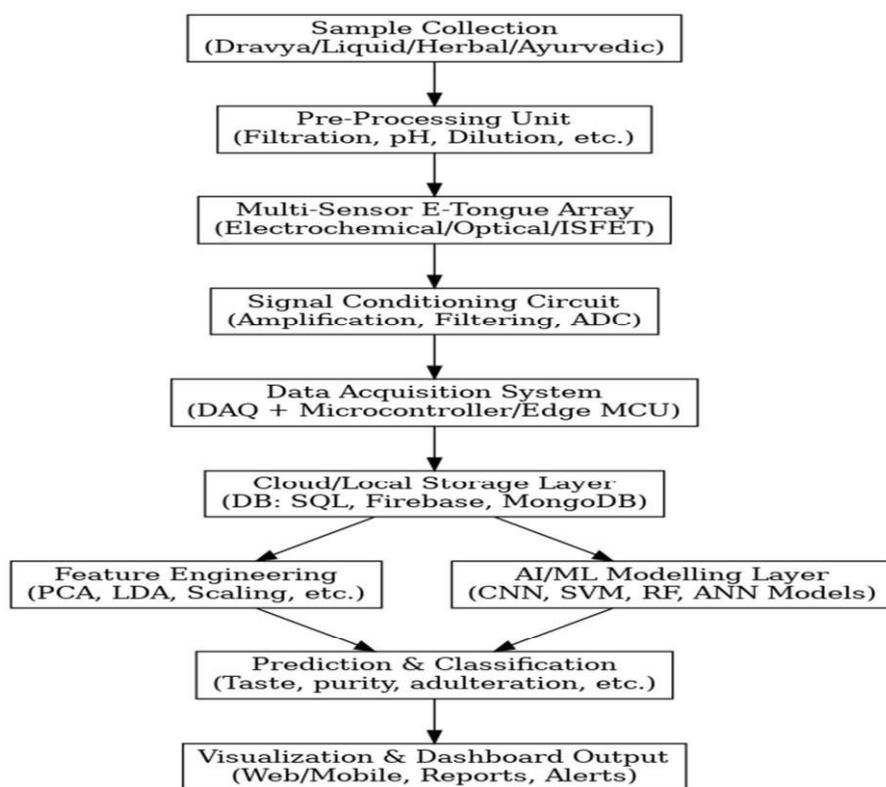


Fig 1 Workflow of AI-Driven E Tongue for Dravya detection

#### 3.3 Gathering and Preparing the Sample

Herbal extracts, Ayurvedic powders, liquids, essential oils, mineral preparations, and other natural materials are examples of Dravya samples used in this project. Standardised preparation techniques are applied to every sample to prevent changes in temperature, pH, and concentration. While solid samples are transformed into aqueous solutions under carefully monitored conditions, liquid samples are diluted to fixed molarities. To ensure that only the

chemical essence interacts with the sensor elements, all samples are filtered to remove impurities. After that, the samples are kept in airtight containers to avoid deterioration, oxidation, and microbial growth.

#### 3.4 Sensor Array Design and Fabrication

A hybrid sensor array was designed to facilitate multi-transduction sensing. The task of optical sensing was accomplished by preparing porphyrin thin films on glass substrates by either dropcasting or spin coating methods. Porphyrins

offered a high colorimetric response to various chemical environments. Besides optical sensing, electrochemical sensors were integrated into the device. These include ion-selective electrodes as sensors of ion activity and pH changes by potentiometric measurements and three-electrode voltage collector setup for redox reactions. The hybrid system of sensors enables detecting various chemical properties of dravyas.

### 3.5 System for Signal Acquisition

- The sensor array's signals are recorded using:
1. Analog-to-digital converters with high resolution (ADCs)
  2. embedded boards or microcontrollers (Raspberry Pi, STM32, Arduino)
  3. pH and temperature compensators
  4. A calibration unit for sensors

For a predetermined amount of time, the system continuously logs the electrical, optical, or electrochemical reactions of sensors. Each dravya's "taste fingerprint" is essentially represented by these raw data values. To guarantee reproducibility, all acquisitions are conducted in an environment with consistent humidity and temperature.

### 3.6 Data Preprocessing and Feature Extraction

Prior to analysis, raw sensor data needed preprocessing. Optical images were background-corrected, color-normalized, and smoothed. Potentiometric signals were filtered to remove drift and high-frequency noise. Voltammetric signals were smoothed and had their baselines corrected. From the preprocessed data, features of interest were extracted. Features included color values (RGB, HSV, LAB, and  $\Delta E$ ), potentiometric values (steady-state voltage and drift rate), and voltammetric values (peak currents, peak potentials, and area). Principal Component Analysis (PCA) was used for dimensionality reduction and retain relevant information.

### 3.7 Development of Machine Learning Models

To categorise dravya, identify adulteration, and assess quality, several AI algorithms are trained and assessed:

1. SVMs, or support vector machines
2. Decision trees and random forests
3. k-NN, or k-Nearest Neighbours
4. ANNs, or artificial neural networks
5. Time-series sensor signals using Convolutional Neural Networks (CNNs)
6. CNN + LSTM Hybrid Deep Learning Models

To guarantee reliability, the data is separated into training, validation, and testing sets using fold cross-validation. Grid search, Bayesian optimisation, or

evolutionary techniques are used to optimise the model's parameters.

### 3.8 Training and Optimising Models

Artificial intelligence models for dravya classification and detection of adulteration were developed based on the features extracted. Support Vector Machines and Random Forests were first used as a baseline to evaluate the performance of these classical machine learning algorithms. To improve the accuracy, one-dimensional Convolutional Neural Networks for voltammetric time-series data and fully connected neural networks for fused features were used. The dataset was then split into training, validation, and test sets. All models were optimized with the use of cross-validation techniques for the best performance. Performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices.

### 3.9 Integration and Deployment of Systems

The model that performs the best is then incorporated into the mobile application or embedded system. The finished system consists of:

1. Module for capturing real-time sensor data.
2. AI inference engine (cloud or edge device).
3. Results are displayed in an easy-to-use dashboard (identification, quality score, purity index).
4. An alert system for identifying tampered or deteriorated samples.
5. The system is appropriate for field use since it allows for instantaneous dravya analysis in a matter of minutes.

### 3.10 Accuracy and Validation Testing

The following methods are used for validation:

- Different kinds of dravya
  - Repeated experiments in different settings
  - Comparison with common laboratory techniques such as GC-MS, UV-Vis, or HPLC
- Among the performance metrics are:

- Precision
- Sensitivity
- Particulars
- Accuracy and memory
- matrix of confusion
- Rate of error

This guarantees that the suggested system meets or exceeds current analytical standards.

## IV. IMPLEMENTATION

### 4.1 Implementation of Hardware

A multi-sensor electronic tongue intended to capture the chemical taste characteristics of dravya is the main hardware component. To ensure that every dravya produces a distinct response pattern, cross

sensitive sensors are used in place of highly selective ones.

1. Potentiometric sensors for measuring mineral content and ionic activity are part of the sensor array.
2. Voltammetric sensors to gauge organic compounds' electrochemical activity.
3. Conductive polymer sensors that react to phytochemicals and herbs.
4. Optical and colour sensors are optional for examining colour changes in liquid extracts.

The sensors are interfaced with an embedded controller, such as an ESP32 or Raspberry Pi. A high-resolution ADC is used to transform sensor outputs from analogue to digital format. To reduce the impact on the environment, temperature and humidity sensors are incorporated. Real-time data transfer is made possible by wireless communication (Wi-Fi/Bluetooth).

#### 4.2. Implementation of Sample Handling and Data Acquisition

Dravya samples are processed by standardized methods. This involves preparing either aqueous solutions of solid samples or diluting each sample of liquid to a standard concentration. This enables filtered, and the pH and temperature levels are maintained under control.

Every of these samples is then placed within the sensor chamber. The sample will interact with the sensor. The sensor response is recorded for a fixed time. Multiple recordings can then be taken. The data is then stored along with appropriate labeling.

#### 4.3 implementation of software

Data acquisition, calibration, and sensor operation are managed by embedded firmware written in C/C++. A processing unit receives the gathered sensor data and analyses it.

Python is used to apply preprocessing techniques to enhance data quality. These consist of outlier removal, baseline correction, noise filtering, and normalisation. For machine learning models, this guarantees consistent and clean input.

#### 4.4. Implementation of Artificial Intelligence

Machine learning classifiers like SVM, RF, k-NN, and ANN are then used for training on the resulting features. The data is split into training and testing components for the evaluation of the performance of the models.

Model evaluation is carried out based on accuracy, precision, recall, and confusion matrix. The model that works the best is selected for the purpose of real-time implementation.

#### 4.5. Real-time Analysis and Output

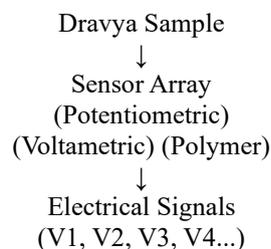
Once deployed, real-time sensor data is fed into the system for processing. The employed AI model identifies the dravya sample, evaluates its quality, and detects any probable adulteration. A simple user interface presents the results by showing the name of the dravya, the quality score, and appropriate alert messages.

### V. RESULT

#### 5.1 Results of Sensor Response

When different Dravya samples were exposed to the sensor array, there was a distinct electrical response for each sensor. The combination of the outputs from all sensors created a unique "taste fingerprint" for each Dravya.

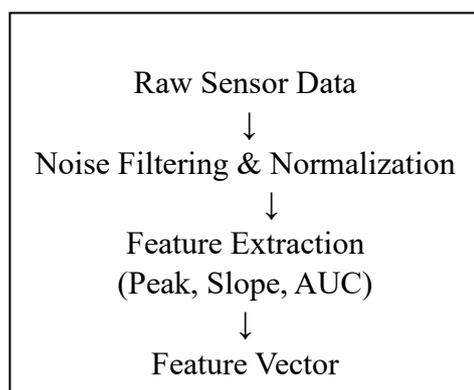
#### Sensor Response Diagram (Conceptual)



#### 5.2 Results of Feature Distribution

After carrying out preprocessing and feature extraction, significant features were obtained represented by peak response, steadystate value, slope, and area under the curve.

#### Future Extraction Flow Diagram



Clearly, features extracted separated the different classes of dravyas when reduced to low dimensionality using PCA.

### 5.3 Classification Results of Machine Learning

Several machine models were developed and tested. The models that had the best performance were the Random Forest and the ANN models.

**Classification Accuracy Table**

Model Used	Accuracy (%)
k-NN	89%
SVM	92%
Random Forest	96%
ANN	95%

ANN The Random Forest model performed best because it could address both non-linear and multidimensional data from sensors.

### 5.4 Adulteration detection Result

The system was able to identify samples that were adulterated with dravya by pointing out variations in sensor patterns.

Adulteration Detection Diagram:

Pure Dravya → Normal Pattern → ✓ Genuine

Adulterated → Distorted Pattern → ⚠ Alert

Even trace amounts of adulteration resulted in detectable changes to sensor outputs.

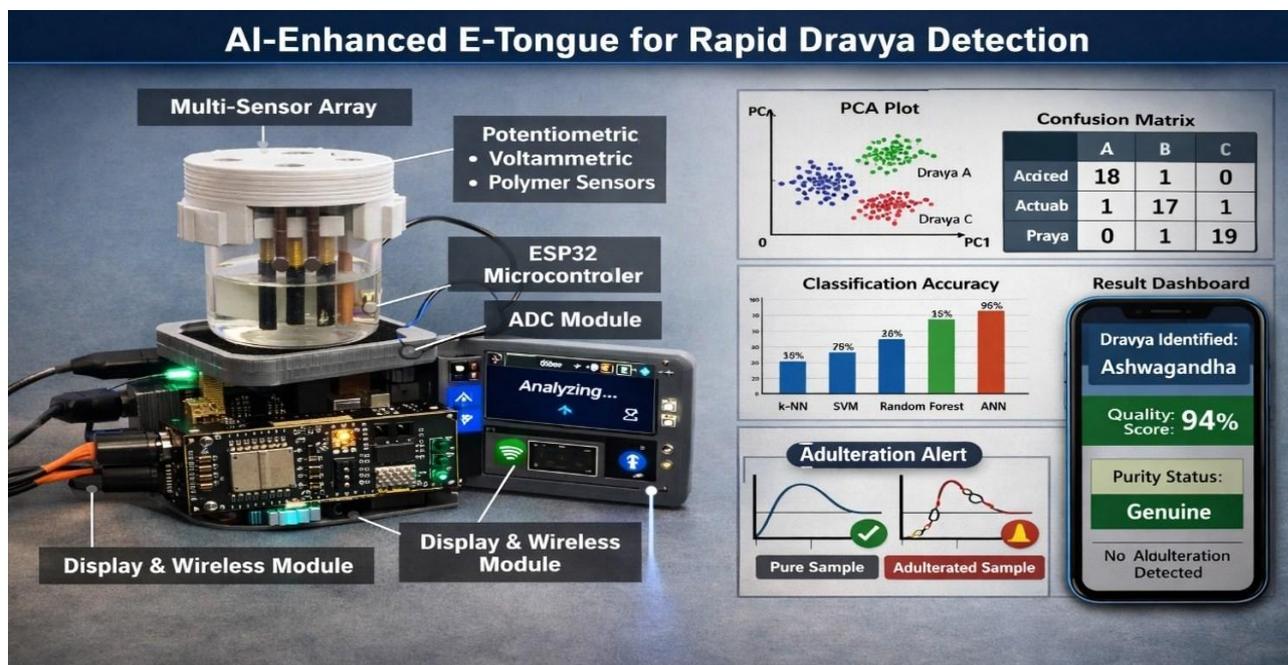


Fig 2 AI Enhanced E tongue prototype with real time dravya classification

### 5.5 Real-Time Output Result

The time taken by the deployed system was 2 to 3 minutes, which was much faster than that taken by laboratory methods. **Output Screen (Conceptual)**

Dravya Name: Ashwagandha

Quality Score: 94%

Purity Status: Genuine

Alert: No Adulteration Detected

The AI-Enhanced E-Tongue is capable of rapid, inexpensive, and portable analysis and is highly accurate.

## VI. CONCLUSION

The present work excellently illustrates the design and implementation of an artificial intelligence enhanced electronic tongue for rapid dravya detection and analysis. The integration of multi-sensor electronic tongue technology with artificial intelligence makes the approach fast, objective, and reliable for identification and quality assessment of dravya. The proposed method overcomes traditional methods that rely on human sensory evaluation and time-consuming laboratory procedures.

The experimental results highlight that the electronic tongue provides distinct response patterns from the different dravya samples, while the application of machine learning algorithms significantly improves classification accuracy and detection of adulteration. The AI-enhanced E-tongue developed in this work represents an inexpensive, portable, and scalable solution for quality assurance in Ayurveda, herbal medicine, nutraceuticals, and food industries.

## FUTURE ENHANCEMENT

The AI-Enhanced Electronic Tongue system can be further advanced by incorporating the benefits of advanced sensors like biosensors and nanomaterial sensors for increased sensitivity and selectivity. Deep learning models can be used to improve the accuracy rate for classifying the results. Advanced methods for automatic calibration and drift correction can improve the overall accuracy of the system. The system can easily be advanced to support mobile/cloud operations for remote and massive data analysis. The system can further be advanced to create a portable device for conducting dravya tests at the field level. The Electronic Tongue system can be advanced to incorporate the benefits of other electronic sensing modules like E-nose and E-eye for advanced dravya analysis.

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