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A comprehensive approach to detecting chemical adulteration in fruits using computer vision, deep learning, and chemical sensors

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ABSTRACT

Contamination of harmful additives in fruits has become a concerning norm these days. Owing to the great popularity of fruits, dishonest vendors frequently use harmful chemicals to contaminate fruits to extend their shelf life, which is extremely dangerous for the general public's health. To mitigate this issue, machine-learning algorithms like Decision Tree Classifier, Naïve Bayes and a deep learning model named "DurbeenNet" are evaluated separately. Alongside, a computer vision-based detection method coupled with a hybrid model is proposed that combines deep learning and chemical sensor. Formaldehyde Detection Sensor is used in this experiment to take reading of the sensor data. Mango, Apple, Banana, and Malta are taken as sample fruits in this study. Sensor data for both fresh and chemical-mixed fruit is newly collected using Formaldehyde Detection Sensor. The above mentioned sensor data along with the previously captures images of both fresh and chemical-mixed state are being integrated to a hybrid model. Among two machine learning algorithms naïve bayes come up with 82 % accuracy. Using both sensor data and captured image data, the proposed model "SensorNet" provides highest accuracy of 97.03 % which is substantial than "DurbeenNet" model's accuracy. Through the utilization of these fruit samples, formaldehyde detection sensor provides instantaneous detection, identifying the specific toxic substances present in the contaminated fruits.

1. Introduction

The detection of toxic substances in fruits is a critical endeavor, paramount to ensuring food safety and safeguarding public health. The prevalence of harmful chemicals, including pesticides and contaminants, in fruits poses significant risks to consumers. Chemical gas sensors have emerged as a promising technology with the potential to detect and quantify these toxic substances in various applications (Gai et al., 2023). By controlling the capabilities of machine learning, deep learning, and hybrid deep learning techniques in conjunction with chemical gas sensors, we can develop accurate and reliable methods for the detection of toxic substances in fruits. In the context of Bangladesh, where fruits are immensely popular and widely consumed, the issue of harmful ingredients in fruits has become a pressing concern. Unscrupulous traders often resort to adding toxic chemicals to extend the shelf life of fruits, which is very hazardous for human health (Proshad et al., 2017). Previous research efforts have proposed a computer vision-based detection process and a hybrid model that combines deep learning and sensor technologies to address this problem. However, there is a clear need for further investigation and innovation to develop an efficient and effective method for the real-time detection of toxic substances in fruits. This motivation underscores the significance of our research, which aims to advance the field by introducing novel approaches for mitigating the risks associated with chemically adulterated fruits and ensuring the safety of fruit consumption in Bangladesh and beyond.

The research problem addressed in this study stems from alarming findings documented by the Association for Human Rights (RDRS) in Dhaka, indicating that a substantial 71 % of fruits in Bangladesh undergo chemical treatment (Mohiuddin, 2019). Beyond the use of formalin, it has been revealed that food is often tainted with melamine

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and methanol to create the illusion of freshness. Furthermore, recent research highlights that the chemicals employed for the artificial ripening of fruits in Bangladesh contain significant quantities of heavy metals and other hazardous compounds. These contaminants permeate fruits, including those with resilient peels, posing severe threats to public health (Hewajulige & Premaseela, 2020). The research problem is further exacerbated by the outcomes of a study conducted by a team of researchers from the Bangladesh University of Engineering and Technology (BUET). Their investigation reveals a distressing truth: artificial ripening not only compromises the safety of fruits but also alters their nutritional composition. This alteration in the nutritional profile of fruits may hinder natural growth processes within the human body and contribute to a range of adverse health effects (Shaheen et al., 2016). Compounding the issue, tests have revealed elevated concentrations of heavy metals and other impurities in samples obtained from the entry points of imported chemicals into Bangladesh (Raknuzzaman et al., 2018). These toxic elements, when present in fruits, pose significant and detrimental health risks to consumers. Therefore, the research problem at hand centers on the urgent need to develop effective methods for the timely and accurate detection of these toxic substances in fruits to safeguard public health. Additionally, the challenges of integrating chemical sensors, deep learning models, and real-time monitoring systems need to be overcome to achieve effective detection results.

The research objectives aim to address the pervasive issue of chemical adulteration in fruits by developing a comprehensive approach that integrates computer vision, deep learning, and chemical sensors. To form a hybrid model, this study involves creating a diverse dataset for Mango, Apple, Banana, and Malta, optimizing deep learning models along with sensor data in both fresh and chemically mixed conditions. The deep learning model will be trained to recognize patterns of chemical adulteration, and hybrid techniques will be explored for enhanced detection. Performance evaluations will validate the reliability of the system, and a real-time detection system will be developed for practical application. The research will also investigate the generalizability across different fruit types, address false positives and negatives, and contribute insights to mitigate health risks associated with chemically contaminated fruits, potentially influencing regulatory measures and industry practices.

This study will find a way to address the following central research questions:

***RQ1**: How can the combined utilization of deep learning and chemical sensors be integrated to develop an accurate and dependable hybrid model for the detection and classification of toxic substances in fruits?*
***RQ2:** What is the effectiveness of the proposed "SensorNet" model compared to other existing deep learning and sensor-based detection techniques in terms of real-time detection systems with chemical gas sensors and advanced computational techniques?*
***RQ3:** How can this integrated approach be customized to enhance the practical applicability of toxic substance detection in fruits, considering the unique challenges posed by environmental factors?*

1.1. List of abbreviations

Acronym	Full Form
RDRS	Association for Human Rights
BUET	Bangladesh University of Engineering and Technology
PLS	Partial Least Squares
SPR	Surface Plasmon Resonance
RIU	Refractive Index Unit
CNN	Convolutional Neural Network
DEDs	Diabetic Eye Diseases
DME	Diabetic Macular Edema
DR	Diabetic Retinopathy
DL	Deep Learning
ML	Machine Learning
ATmega328P	A type of 8-bit microcontroller
GPU	Graphics Processing Unit
k-fold	k-Fold Cross-Validation

2. Background study

To provide a comprehensive overview of the existing literature and position our research within the current landscape, we have reviewed several key studies related to sensor and image-based classifications. The following table categorizes these works along their main distinctive characteristics, such as focus area, methodology, key findings, and contributions. This summary helps to highlight the relevance of these studies to our research on detecting toxic substances in fruits using chemical gas sensors and advanced computational techniques.

Author(s)	Year	Focus Area	Methodology	Key Findings	Contributions
Rehan Saeed, et al.	2022	Fish Quality Evaluation	Mechanistic Review	Insights into sensor-based and ML techniques for fish quality	Review of sensor and ML integration; future perspectives
Tian Gan, et al.	2013	Trace Colorants Detection in Food	Experimental Study	Sensor detects colorants with high sensitivity	Effective sensor technology for food colorants
Abdus Sattar, et al.	2024	Toxic Substances Detection in Fruits	Deep Learning, Computer Vision	Proposed DurbeenNet model achieves 96.71 % accuracy	Introduced a novel DurbeenNet model to detect with high accuracy
Mohamed K. Morsy, et al.	2015	Fish Spoilage Monitoring	Colorimetric Sensor Array	Tracks spoilage indicators	Real-time spoilage assessment method
Harikesavan Thenmozhi, et al.	2018	Carcinogenic Substances Detection in Food	SPR-based Photonic Crystal Fiber Senso	High spectral sensitivity for carcinogens	Advanced sensitivity of SPR-based sensors
Mohammad Bordbar, et al.	2018	Toxic Substances in Food Samples	Colorimetric Sensor Array, PLS Regression	Detected alum and synthetic acetic acid accurately	Accurate detection in adulterated food using sensors
Joyati Das, et al.	2022	Food Pathogens and Contaminants Detection	Review	Overview of various sensor technologies	Highlights sensor improvements in food hazard detection

To establish a comprehensive foundation for our research, we have conducted an in-depth review of key studies related to sensor and image-based classification techniques. The following detailed background study examines significant contributions in the fields of fish quality evaluation, trace colorant detection in food, toxic substances detection in fruits, fish spoilage monitoring, carcinogenic substances detection in food, and food pathogens and contaminants detection. Each of these studies offers valuable insights and advancements that are pertinent to our research on detecting toxic substances in fruits using chemical gas sensors and advanced computational techniques. The subsequent sections provide a thorough analysis of these works, highlighting their methodologies, key findings, and contributions to the field.

Rehan Saeed, et al. (Saeed et al., 2022) recently presented a mechanistic review centered on the integration of sensors and machine learning for fish quality evaluation. Their research sheds light on the dynamic field of fish quality monitoring, harnessing a range of detection sensors, including colorimetric, electrochemical, enzyme, and gas sensors. This comprehensive review offers valuable insights into the assessment of fish quality through the combined utilization of detection sensors and machine learning models. The study not only delves into the diverse array of fish quality indicators but also underscores the transformative potential of sensor-based approaches when coupled with sophisticated machine-learning techniques. Furthermore, the authors of this review place a strong emphasis on addressing current challenges and charting the path toward future perspectives in this evolving domain. Their work serves as a pivotal reference point for understanding the intricate interplay between sensor technologies, machine learning, and the assessment of food quality, which resonates with our research endeavor focused on detecting toxic substances in fruits using chemical gas sensors and advanced computational techniques.

Tian Gan, et al. (Gan et al., 2013) conducted an insightful investigation focused on the simultaneous determination of trace colorants in food. Their pioneering approach hinged on the utilization of graphene and mesoporous TiO_2 within an electromagnetic sensor framework. This study resulted in the development of a sensor system tailored for the detection of sunset yellow and tartrazine, two significant colorants in food products. The sensor showed clear square-wave voltammetric peaks, especially at 272 mV. This was because graphene and mesoporous TiO_2 are very good at collecting charges and breaking them down. The study also found that the higher the response peak for dusk yellow and tartrazine, the higher their concentrations were, which were between 0.02–2.05 μM and 0.02–1.18 μM, respectively. Notably, this method highlighted remarkable sensitivity, with detection limits as low as 6.0 nM for sunset yellow and 8.0 nM for tartrazine. The work of Tian Gan and colleagues underscores the potential of advanced sensor technologies in the detection of toxic substances within food items, especially colorants. Their results show how important it is to have accurate and sensitive detection methods. This is a theme that is very similar to our research goal, which is to use chemical gas sensors and cutting-edge computer methods to create effective detection methods for toxic substances in fruits.

Abdus Sattar et al. (Sattar et al., 2024) introduced a computer vision-based deep learning approach to detect toxic substances. They classify four different types of fruits in this study. Different data augmentation techniques were used to enhance the dataset. The authors have employed GoogleNet, DenseNet, VGG16, and ResNet50 models, along with a novel model, to compare the accuracy of detecting toxic substances in fruits. Among these pre-trained deep learning models, their proposed model, DurbeenNet, outperformed all other models. The accuracy they have achieved for their proposed model to detect whether a fruit is mixed or not is 96.71 %. The research aims to enhance public health, recommend food safety regulations, and mitigate health risks associated with the consumption of chemically contaminated fruits.

Mohamed K. Morsy, et al. (Morsy et al., 2016) have introduced a noteworthy contribution to the field of food quality monitoring, specifically in the context of fish spoilage. Their research revolves around the development and validation of a colorimetric sensor array designed for the real-time assessment of fish spoilage. This new method involved testing sixteen chemo-sensitive compounds, which led to the discovery of key signs of spoilage like trimethylamine, dimethylamine, cadaverine, and putrescine. The colorimetric sensor array was employed to track the progression of fish deterioration over nine days, with a focus on the critical 24-hour period at room temperature. The research also found a strong link between the colorimetric array's signal intensity and changes in pH levels and thiobarbituric acid levels over time. The work of Mohamed K. Morsy and collaborators not only underscores the potential of sensor arrays for monitoring food quality but also highlights the importance of understanding the underlying chemical changes associated with spoilage. This aligns closely with the objectives of our research, which seeks to leverage chemical gas sensors in tandem with machine learning and deep learning techniques for the detection of toxic substances in fruits, thereby enhancing food safety and public health.

Harikesavan Thenmozhi, et al. (Thenmozhi et al., 2019) have introduced a noticeable development in the field of sensor technology for the identification of carcinogenic substances in food and cosmetics. Their creative contribution is the application of a surface plasmon resonance (SPR)–based, d-shaped photonic crystal fiber (PCF) sensor. The authors did research that got an amazing maximum spectral sensitivity of 50,000 nm/RIU using a high resolution of $4 \times 10{-}4$ RIU. Furthermore, their sensor, which had a sensitivity of 1266.67 RRIU1, showed remarkable efficacy. The model that has been suggested showcases the potential of d-shaped PCF structures and emphasizes their exceptional sensitivity, especially in the near-infrared (IR) spectrum. Furthermore, the study investigated how to alter the widths of the air holes and core to maximize sensor performance. This work stands out from the competition because it offers more sensitivity than previous SPR sensors, highlighting the value of cutting-edge sensor technologies in improving the accuracy of harmful material detection. This is in line with our study, which aims to strengthen public health and food safety by combining chemical gas sensors with machine learning and deep learning to identify hazardous materials in fruits.

Harsh Kumar, et al. (Kumar et al., 2020) have contributed a comprehensive review in the field of food safety, focusing on the sensor-based detection of foodborne pathogens and employing the advancements in nanotechnology. The urgency of this research emanates from the profound health risks associated with the consumption of food contaminated by microorganisms, leading to severe foodborne diseases. To address these pressing issues, the authors emphasize the critical need for precise detection and identification of toxins and pathogenic microbes in food. Their approach centers on the innovative concept of bio-sensing, which has empowered researchers to develop nano-biosensors utilizing various nano-materials and composites. This strategy not only enhances the responsiveness of detection but also augments the specificity of locating microorganisms. They have also highlighted the significance of sensor technologies and nanotechnology in food safety, shedding light on the importance of meticulous detection methodologies for safeguarding public health. This perspective aligns closely with our research agenda, which incorporates chemical gas sensors, machine learning, deep learning, and hybrid deep learning approaches for the detection of toxic substances in fruits, ultimately contributing to enhanced food safety and consumer well-being.

Tahir Ul Gani, Mir et al. (ul Mir et al., 2023) have introduced a detection process for sensitive samples using portable sensors to advance biological investigations. They have mentioned a potent diagnostic tool for examining biological samples of complicated complexity. By employing biomolecules, including proteins, nucleic acids, microorganisms or microbial products, antibodies, and enzymes, these biosensors provide sensitive detection capabilities. The authors have also mentioned that forensic investigations and criminal prosecutions are essential because of their quickness, precision, stability, specificity, and affordability. Notably, portable biosensors have been created with the ability to quickly identify explosives, toxins, poisons, and bodily fluids. These sensors have proven to be extremely useful in forensic analyses of suspicious materials, producing accurate findings that facilitate speedy and impartial legal proceedings. One of the main benefits the authors have claimed is that portable biosensors have the capacity to identify forensic evidence in a sensitive and non-destructive manner without the need for lengthy sample preparation, which lowers the likelihood of inaccurate findings.

Mohammad Bordbar, et al. (Bordbar et al., 2018) have made a valuable contribution to the field of toxic substance analysis, particularly in the context of adulterated fruit pickle samples. Their research focuses on employing a colorimetric sensor array for both qualitative and quantitative assessments of toxic materials within these samples. The authors successfully detected two prominent toxic elements, namely alum and synthetic acetic acid, using the colorimetric sensor array. To estimate the precise content of alum and synthetic acetic acid within pickle samples, they utilized partial least squares (PLS) regression as a multivariate calibration method. Through this approach, they achieved notable results, with root mean square errors for calibration and prediction measured at 0.469 and 0.446 for alum and 1.34 and 0.933 for acetic acid, respectively. The work of Mohammad Bordbar and colleagues displays the potential of sensor-based techniques for the accurate and comprehensive detection of toxic substances in food samples. Their use of multivariate calibration fits with our research goals, which involve combining chemical gas sensors with cutting-edge computer methods, such as machine learning, deep learning, and hybrid deep learning approaches, to make it easier to check the safety and quality of fruits while protecting public health.

Joyati Das, et al. (Das & Mishra, 2022) proposed a review of different sensors for detecting food pathogens, contaminants, and toxins. Here, the authors have focused on efficient detection techniques for food hazards that are deemed essential to ensuring food safety, with various methods having been established for sensing food hazards to address safety-related challenges. They have also mentioned that the trace levels of food contaminants, pathogens, and toxins have challenged the development of efficient and reliable detection techniques. Due to their sensitivity, speed, and portability, the use of novel and quick sensors as sensing tools has accelerated the development of food safety assays. This review talks about the harmful effects of food pathogens, mycotoxins, and food contaminants like pesticides, acrylamide, food allergens, and antibiotics. It also talks about how different sensors (like fluorescence sensors, colorimetric sensors, biosensors, and electronic nose sensors) work and how they have improved over the last 5 years to find food hazards. Moreover, the authors claimed that the applications of these four types of sensors for detecting food pathogens, mycotoxins, and food contaminants are novel.

Shikha Sharma et al. (Sharma et al., 2022) have presented an assessment using machine learning and deep learning aproach along with application. They have mentioned that a large amount of data is generated nowadays but most of them are not useful. Conventional approach is unable to find insights from those vast amount of data. To obtain meaningful data, it's necessary to integrate certain techniques into existing datasets that prove effective for real-world applications. Authors have suggested an application based on machine learning and deep learning, which processes data and generates patterns for decision-making by mimicking the functioning of the human brain. The aim is to investigate the research applications and commonly utilized methods within the fields of machine learning and deep learning.

Meenakshi Aggarwal et al. (Aggarwal et al., 2023) have introduced a machine learning and deep learning based classification of rice leaf diseases. They have raise their concern for ailments and infections in plants. They also mentioned that, plant diseases significantly impact agricultural production, directly affecting a country's overall crop yield. To overcome this issue, authors have proposed a deep learning based effective and appropriate technique to classify various rice leaf diseases. Initially, they have achieved the classification using machine and ensemble learning classifiers. Authors have compared the accuracy with different CNN and Transfer Learning models. Among all the applied models they have got highest accuracy of 88 % for InceptionResNetV2. They have concluded that Transfer learning model outperforms the machine learning classifiers in their study.

Seema Gulati et al. (Gulati et al., 2023) reviewed a comprehensive analysis on diabetic eye disease classification and detection using deep learning. Diabetic affected patients frequently experience eye ailments stemming from elevated sugar levels. That is why authors have realized the necessity of an automatic detection system for such eye diseases because manual detection is boring and it also requires high level of experience. To mitigate this, they have presented a review of existing systems designed for the detection and categorization of Diabetic Eye Diseases (DEDs), including Diabetic Macular Edema (DME), Diabetic Retinopathy (DR), Glaucoma, and Cataracts. Due to the ability of handling large dataset, Deep Learning (DL) provides high accuracy for fundus images of the eye. But authors have also mentioned that the accuracy of their classification can be improved by fine-tuning with the help of data augmentation.

In some recent research, scientists have been looking at ways to figure out how the quality of different foods can be increased (Elayanithottathil, 2020; Kamuni et al., 2022; Saha et al., 2023; Ren et al., 2019). They're using different tools and methods to measure things like size, color, and taste to help farmers and sellers know when those foods are at their best. On the other hand, other studies (Bedair et al., 2022; Gai et al., 2023; Kalyani et al., 2020; Mohiuddin, 2019; Wilson, 2021) have focused on finding ways to check if there are any bad chemicals in vegetables. They're using special sensors to quickly detect things like pesticides or harmful metals, which helps keep our food safe to eat. These research efforts are all about making sure the fruits and vegetables we eat are top-notch and healthy for us. Moreover, (Barry, 2022; Kumar et al., 2021; Shaban et al., 2023; Yaroshenko et al., 2020) has focused on real-time water quality monitoring using sensors.

While several studies have contributed valuable insights into the detection of toxic substances in fruits using sensor technologies, certain practical challenges and opportunities for further research remain pertinent. Firstly, practical challenges related to the deployment of sensor-based detection systems in real-world fruit markets and supply chains need to be thoroughly addressed. This includes aspects like sensor calibration, adaptability to varying environmental conditions, robustness against potential interferences, and the consideration of cost-effectiveness. In-depth exploration of these factors is essential to ensuring the feasibility and scalability of the proposed approaches, bridging the gap between research findings and practical implementation. Furthermore, there is potential for enhancing detection accuracy and reliability by integrating multiple sensor technologies within a single detection system. While the reviewed studies have individually explored various sensor modalities, such as colorimetric, electrochemical, enzyme, and gas sensors, there appears to be a research gap in terms of harnessing the synergistic effects of combining these technologies. Researchers are looking into how to use a mix of different types of sensors and possibly combine them with advanced computer methods such as machine learning, deep learning, and hybrid deep learning. This could improve the accuracy of finding harmful substances in fruits. To our knowledge, prior research efforts have primarily focused on either machine learning or sensor-based technologies in isolation. This paper aims to bridge this gap by proposing an integrated approach that leverages chemical gas sensors and advanced computational methods to achieve a comprehensive and effective solution for detecting toxic substances in fruits.

3. Materials and methodology

3.1. Arduino Uno

The Arduino Uno has earned widespread popularity as a microcontroller development board, largely due to its user-friendly design and versatility. At its core is the 8-bit ATmega328P microcontroller, which serves as the brain of the board (Sudhan et al., 2015). Complementing this central processing unit, the Arduino Uno incorporates various essential components in Fig. 1. A crystal oscillator is integrated to ensure precise timing and synchronization of operations. Serial communication capabilities enhance its connectivity, enabling seamless interaction with other devices and facilitating data transfer. The inclusion of a voltage regulator is crucial for maintaining a stable power supply, ensuring that the microcontroller operates reliably within its specified voltage range. This thoughtful combination of components not only supports the ATmega328P but also makes the Arduino Uno a well-rounded and accessible platform for a diverse array of electronic projects and applications.

To detect toxic substances in fruits using a sensor-based integrated hybrid deep learning approach, we have taken the four sample fruit

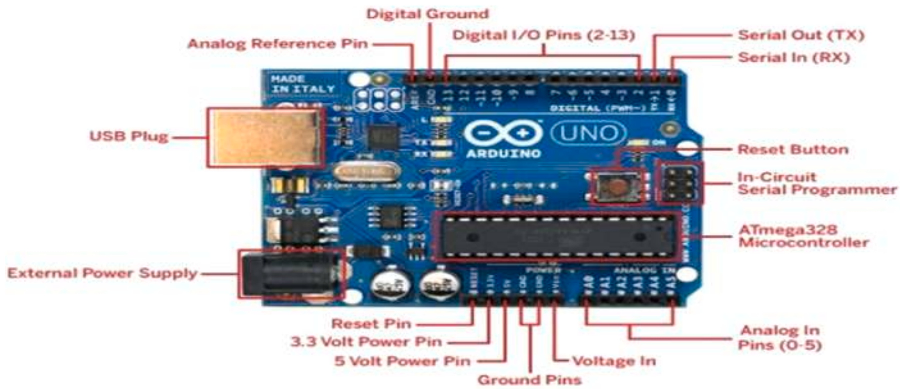

Fig. 1. Pin configuration of Arduino UNO (Agarwal, 2024).

images of Apple, Malta, mango, and bananas in both fresh and chemically mixed states, which were collected from a previous research dataset. Afterward, the sensor data is taken using a formaldehyde detection sensor. Fig. 2 denotes the methodology steps for applying the machine learning algorithms.

- *Sensor Data:* The journey begins with the collection of sensor data. Chemical gas sensors interact with the selected fruit samples and generate a rich dataset comprising numerical information about the composition and concentration of toxic substances within the fruits.
- *Preprocessing:* This is the process of getting datasets ready for feature selection and feature extraction. After preprocessing, the dataset can be used to fit into a model for the prediction.
- *Feature Selection:* In this stage, we strategically identify and select relevant features from the sensor data. Feature selection is a critical step in optimizing the performance of our detection model, as it helps narrow down the dataset to the most informative attributes.
- *Feature Extraction:* Building on the selected features, we employ feature extraction techniques to transform the data into a more meaningful representation. Feature extraction aids in capturing essential patterns and characteristics from the raw sensor data, enhancing the discriminative power of our model.

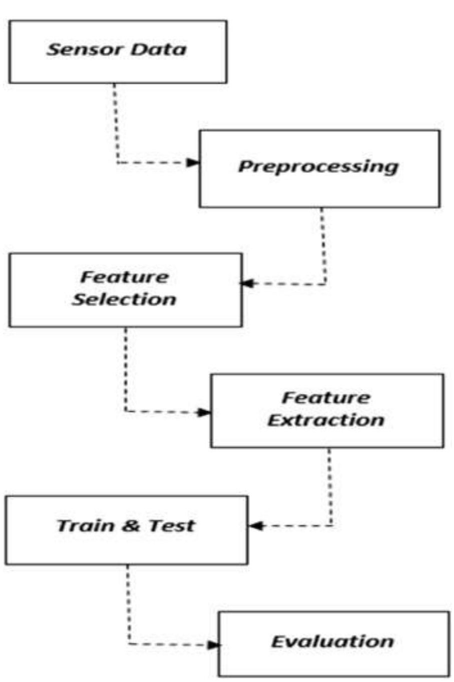

Fig. 2. Methodology steps for ML models.

- *Train and Test:* The transformed data is then fit into our classification model. This model, built using machine learning approaches, is trained to recognize and classify toxic substances based on the extracted features. The model learns from the sensor dataset to make predictions.
- *Evaluation:* The final stage of our methodology yields the output. The classification model processes the sensor data and produces results that indicate the presence or absence of toxic substances in the fruit samples. These results are conveyed as the output of our system.

By following this methodology, we aim to develop a robust and efficient system for the real-time detection of toxic substances in fruits. The careful selection and extraction of relevant features, coupled with advanced classification techniques, enable us to provide accurate and actionable insights to ensure food safety and protect public health.

3.2. Image data collection

The initial step in our research process involves the deliberate selection of sample fruits. This careful curation aims to encompass a representative set of fruits commonly found in Bangladesh, specifically Mango, Apple, Banana, and Malta (Citrus × sinensis). These fruits are chosen due to serve as the foundational elements of our data collection endeavors. They are emblematic of the diverse array of fruits prevalent in the region and are, unfortunately, highly susceptible to chemical adulteration. Fig. 3 displays the sample data of fresh and chemical mixed fruits.

3.3. Sensor data collection

To enable real-time detection of toxic substances, we incorporate a chemical detection sensor named “Formaldehyde Detection Sensors”. With the help of this sensor, we have taken sensor data for both fresh and chemical mixed conditions for each of the four types. After collecting the sensor data, it is loaded for preprocessing. Fig. 4 displays the collected sensor data for each fruit class along with targeted class.

This research involves the strategic integration of chemical detection sensors with the selected sample fruits to enable real-time detection of toxic substances. These sensors encompass a diverse array, including Formaldehyde Detection Sensors. The critical objective of this integration is to facilitate meaningful interactions between these sensors and the sample fruits, thereby generating essential data concerning the presence of toxic chemicals within the fruit samples. In Fig. 5 denotes the procedure of formaldehyde sensor reading steps from fruits.

The key fact of our data collection process revolves around the instant detection of chemicals within the sample fruits. This rapid detection is made possible through the utilization of chemical sensors, which come into direct contact with the fruit samples. These sensors promptly and decisively identify the specific toxic substances present

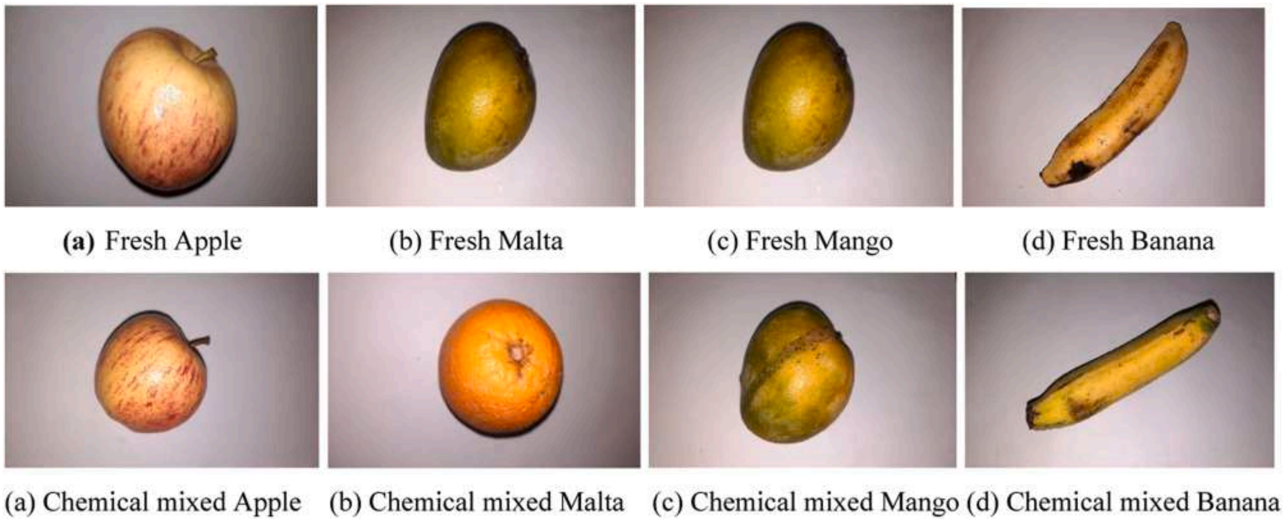

Fig. 3. Sample of fresh & chemical mixed fruits (Morsy et al., 2016).

	fresh_apple	mixed_apple	fresh_malta	mixed_malta	fresh_mango	mixed_mango	fresh_banana	mixed_banana	harmful
0	28	88	30	97	33	79	33	70	No
1	28	90	30	98	32	80	33	69	No
2	28	89	30	100	33	79	33	69	No
3	28	88	30	99	33	80	32	69	No
4	28	90	30	99	32	80	33	69	No
...	...	...	...	...	...	...	...	...	...
95	27	95	29	110	30	78	30	76	No
96	27	95	30	110	30	78	30	76	No
97	27	95	30	111	30	78	30	76	No
98	27	95	30	110	30	78	30	75	No
99	27	95	30	111	30	78	30	75	No

Fig. 4. Sample of collected sensor data.

within the contaminated fruits. This real-time dimension of our data collection process assumes paramount importance as it enables us to assess swiftly and proactively address potential health risks associated with the consumption of these fruits.

- **Machine Learning and Deep Learning Integration:** To enhance the effectiveness of our data collection process, we employ machine learning, deep learning, and hybrid deep learning techniques. These computational methodologies aid in the analysis of the data generated by the chemical sensors, enabling us to detect and classify toxic substances with precision and accuracy.

In summary, our data collection process constitutes a holistic and innovative approach to mitigate the health risks of chemically adulterated fruits in Bangladesh. By synergizing machine learning, deep learning, and hybrid deep learning techniques with chemical gas sensors, we aim to provide a comprehensive solution for the effective detection of toxic substances, ultimately safeguarding public health and ensuring the safety of fruit consumption in the region.

The architectural diagram for our research explicates the fundamental components and processes involved in our approach to toxic substance detection in fruits using chemical gas sensors, machine learning, deep learning, and hybrid deep learning techniques.

Fig. 5. Procedure of formaldehyde sensor reading.

- ***Chemical Gas Sensor:*** This foundational element represents the core of our detection system. Chemical gas sensors are strategically deployed to interact with the selected fruit samples. These sensors possess the capability to detect and quantify specific toxic substances present within the fruit.
- ***Selected Fruit:*** The selected fruit serves as the subject of our analysis. It encompasses a wide variety of fruits susceptible to contamination by toxic substances. These fruits are chosen to represent real-world scenarios and challenges encountered in fruit markets.
- ***Numeric Data:*** As the chemical gas sensor interacts with the selected fruit, it generates a stream of numeric data. This data encapsulates vital information about the composition and concentration of toxic substances present in the fruit.
- ***Real-Time Detection:*** The data generated by the chemical gas sensor undergoes real-time analysis and processing. This stage is pivotal in ensuring swift and accurate detection of toxic substances within the fruit samples. It involves the utilization of machine learning, deep learning, and hybrid deep learning approaches.

Our proposed system leverages the power of these advanced computational techniques to analyze the numeric data generated by the chemical gas sensors. These methods enable us to develop accurate and reliable models for the detection and classification of toxic substances. The real-time aspect of our system ensures that the detection process is both timely and responsive to changes in the fruit samples. In summary, our architectural diagram illustrates the flow of information and processes from the initial interaction of chemical gas sensors with selected fruits to the generation of numeric data and its subsequent analysis using machine learning, deep learning, and hybrid deep learning approaches. This integrated system represents our innovative solution for enhancing food safety and safeguarding public health by effectively detecting toxic substances in fruits.

3.4. Applied methods

The method applied for toxic substances detection with chemical gas sensors using machine learning, deep learning, and hybrid deep learning approaches involves several key steps. Firstly, a dataset of gas sensor readings, including responses to toxic substances, is collected and preprocessed. Relevant features from the sensor data may be extracted using feature engineering approaches. Next, a baseline model for the identification of dangerous substances is constructed using machine learning techniques.

3.4.1. Machine learning algorithms

i) **Decision Tree Classifier**

The Decision Tree Classifier is a dynamic supervised learning method effective for both classification and regression problems (Sagu, 2020). It creates a hierarchical tree structure, with each leaf node corresponding to a predicted class label and each inside node representing a judgment based on a particular attribute. In order to optimize homogeneity within each subset, the algorithm attempts to partition the data into subsets recursively.

a) *Algorithm Overview:*

Given a dataset DD with features XX and corresponding labels YY, a decision tree is constructed by recursively partitioning the data based on feature values. Let XiXi be the ii-th feature and YY be the target variable. At each internal node tt, the decision is made by evaluating a splitting criterion, such as Gini impurity or entropy. The chosen criterion measures the impurity of the data at a node, and the split is made to minimize this impurity.

a) *Gini Impurity:*

$$\mathrm{G(t)} = 1 - \sum i = \mathrm{1c(pi)2G(t)} = 1 - \sum i = \mathrm{1c(pi)2}$$

where cc is the number of classes, and pipi is the proportion of samples in class ii at node tt.

a) *Entropy:*

$$\mathrm{H(t)} = - \sum i = \mathrm{1cpi{\cdot}log2(pi)H(t)} = - \sum i = \mathrm{1cpi{\cdot}log2(pi)}$$

where pipi is the same as defined for Gini impurity.

The information gain is then calculated to determine the best feature to split on:

$$\begin{aligned}\text{Information Gain} &= \text{Current Impurity} \\ &\qquad - \sum \mathrm{jNjN{\cdot}Impurity(j)Information\ Gain} \\ &= \text{Current Impurity} - \sum \mathrm{jNNj{\cdot}Impurity(j)}\end{aligned}$$

where NN is the total number of samples at the current node, NjNj is the number of samples in the jj-th child node, and Impurity(j)Impurity(j) is the impurity of the jj-th child node.

a) *Termination Criteria:*

The tree-building process continues until a predefined stopping criterion is met, such as reaching a maximum depth or a minimum number of samples at a node.

i) **Naive Bayes:**

The Naive Bayes Classifier is a probabilistic algorithm based on Bayes' theorem with the "naive" assumption of feature independence (Wibawa et al., 2019). It is particularly effective for classification tasks, leveraging probabilities to predict class labels.

a) *Algorithm Overview:*

Given a dataset DD with features AA and corresponding labels BB, the Naive Bayes Classifier computes the posterior probability of a class given the observed features using Bayes' theorem:

$$\mathrm{P(B|A)} \;=\; P\mathrm{(A|B){\cdot}P(B)P(A)P(B|A)} \;=\; P\mathrm{(A)P(A|Y){\cdot}P(B)}$$

where P(B|A) P(B|A) is the posterior probability, P(A|B)P(A|B) is the likelihood, P(B)P(B) is the prior probability, and P(A)P(A) is the evidence.

a) *Naive Assumption:*

The "naive" assumption simplifies the computation by assuming independence among features, leading to

$$\begin{aligned}\mathrm{P(A|B)} &= P\mathrm{(A1|B){\cdot}P(A2|Y){\cdot}\ldots{\cdot}P(An|B)P(A|B)} \\ &= P\mathrm{(A1|B){\cdot}P(A2|B){\cdot}\ldots{\cdot}P(An|B)}\end{aligned}$$

where $A_1, A_2, \ldots, A_n$ $A_1, A_2, \ldots, A_n$ are the individual features.

a) *Parameter Estimation:*

To make predictions, the algorithm estimates the parameters $P(A_i|B)$ $P(A_i|B)$, and P(B)P(B) from the training data. For continuous features, it often assumes a probability distribution, such as Gaussian or multinomial.

3.4.2. Deep learning model

3.4.2.1. DurbeenNet. A 23-layer architecture known as "DurbenNet" includes input, convolutional, pooling, flatten, fully connected, and output layers, among other layers (Sattar et al., 2024). The pooling layer reduces the dimension of the derived feature matrix, whereas the convolutional layer is used to extract picture information in matrix form. Using linked neurons, the flattened and completely connected layers function as classification components, recognizing or classifying pictures. Fig. 6 displays the basic architecture of the deep learning model.

This classifier model employs multiple Convolutional Layers to identify its important features when it receives an image and forms feature matrixes The Pooling Layer then reduces this feature matrix. For this, we make use of the Maximum Pooling Layer. After the 2D matrix has been reduced, it is converted into a straight line using the Flatten layer. Subsequently, all of the related layers interface at each point along this line to determine whether or not formalin has been mixed in with the natural products. To determine whether the fruit contains anything harmful is like putting pieces of a puzzle together.

3.4.3. Hybrid model

3.4.3.1. SensorNet. The model “SensorNet” is a 23-layer design architecture that consists of different layers like a convolutional layer, pooling layer, flatten layer, and fully connected layers that blend the qualities of picture investigation with sensor information handling. Instead of taking only images as sample input, this model also takes sensor data along with the images. All the layers extract features from different fruit sample images and form a feature matrix. After reducing the matrix size using the max-pooling layer, it converts the 2-dimensional matrix into a 1-dimensional array, which is remarked as flatten layer. On the other hand, sensor data is also taken as input along with the images. After preprocessing, sensor data directly goes to flatten layer and combines with the extracted feature matrixes. Furthermore, the fully connected layer connects all the flatten layers to dense layers to make the classification. Fig. 7 displays the basic architecture of our proposed hybrid model, “SensorNet.”

The computational complexity of the SensorNet model involves analyzing both the deep learning component, which processes image data, and the integration component, which processes sensor data. For the deep learning component, SensorNet employs a series of convolutional layers, pooling layers, and fully connected layers to extract features from images of fruits. The computational complexity of each convolutional layer is determined by the number of filters (K), the dimensions of the output feature map (M and N), and the size of the filter (D). Specifically, the complexity can be expressed as $O(K.M.N.D^2)$. Pooling layers, which reduce the spatial dimensions of the feature maps, have a lower computational burden but still contribute to the overall complexity. The flatten layer then converts the 2-dimensional matrices into 1-dimensional arrays, preparing them for the fully connected layers.

The sensor data component involves preprocessing the sensor readings and then integrating them with the features extracted from the images. This integration typically occurs at the flatten layer, where the sensor data is combined with the image-derived feature arrays. The complexity of processing the sensor data depends on the preprocessing steps and the size of the data, but it is generally less intensive compared to the deep learning component. The final classification is handled by fully connected layers, which combine the features from both the image data and the sensor data. The computational complexity of the fully connected layers is $O(N.M)$, where N and M are the number of input and output neurons, respectively.

Overall, the computational complexity of SensorNet is the sum of the complexities of the deep learning feature extraction, the sensor data preprocessing, and the final fully connected layers. While this makes SensorNet computationally intensive, modern deep learning frameworks and hardware accelerators, such as GPUs, can manage the processing load effectively.

4. Results and discussion

4.1. Machine-Learning algorithms evaluation

4.1.1. Decision tree classifier

The loaded dataset was divided into training and testing subsets, with the former used to train the decision tree classifier, a supervised learning algorithm that constructs a tree-like structure based on features and their respective decisions, ultimately aiming to classify instances into predefined classes. The k-fold cross-validation method was used to train and test the dataset. In this approach, the data was divided into k subsets. Each subset was used once as a test set while the remaining k-1 subsets were combined to form the training set. This process was repeated k times, ensuring that every subset was used for testing exactly once. During training, the classifier learned patterns and relationships within the data. Following this, the classifier’s performance was evaluated using the testing set, where predicted class labels were compared with actual labels to calculate accuracy. Achieving an accuracy of 79.83 %, the classifier correctly classified nearly 80 % of instances in the testing set. Further optimization, such as adjusting parameters or employing pruning techniques, could potentially enhance its performance. Overall, this process enabled effective training and evaluation of the decision tree classifier on the sensor dataset.

4.1.2. Naïve bayes

The loaded dataset was divided into training and testing subsets using the k-fold cross-validation method. In this approach, the data was split into k equal parts. Each part was used once as a testing set, while the remaining k-1 parts were used for training. This process was repeated k times to ensure thorough evaluation of the model. In the training phase, the Naive Bayes classifier, a probabilistic supervised learning model that assumes independence between features, was trained to categorize instances into predefined classes. Throughout this process, the classifier learned underlying patterns and relationships

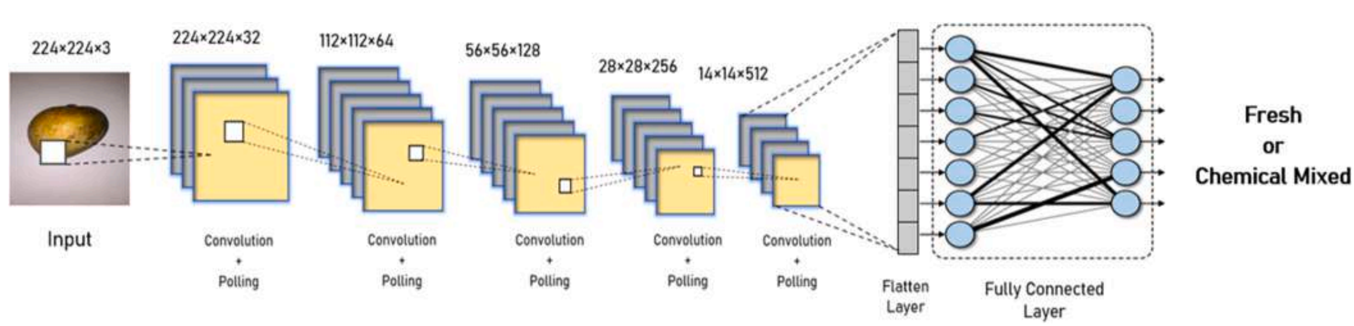

Fig. 6. Basic architecture of deep learning model (Sattar et al., 2024).

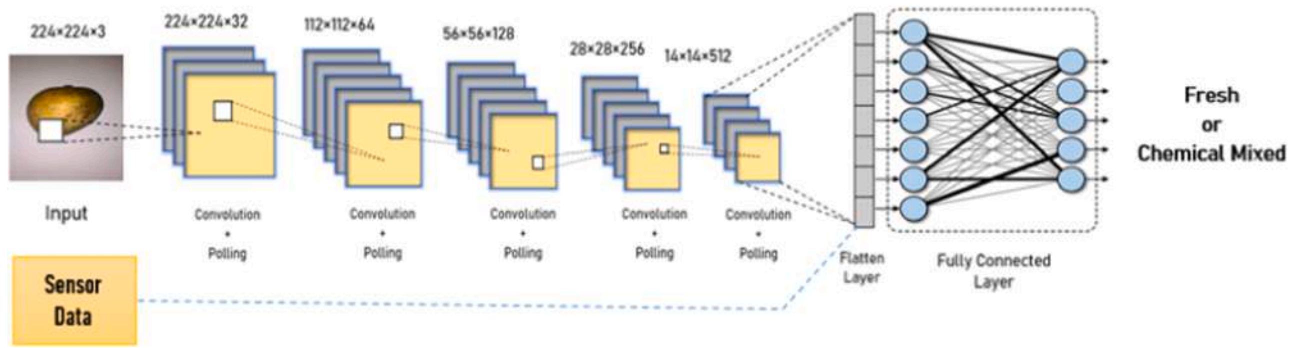

Fig. 7. Basic architecture of integrated hybrid model.

within the dataset. Subsequently, its performance was assessed using the testing set, where predicted class labels were compared to actual labels to determine accuracy. Achieving an accuracy rate of 81.92 %, the classifier successfully classified nearly 82 % of instances in the testing set. Further improvements, such as parameter tuning or feature engineering, could potentially enhance its effectiveness, the same as the decision tree classifier. In essence, this approach enabled the thorough training and evaluation of the Naive Bayes classifier on the sensor dataset.

Among both the machine-learning algorithms, Naïve Bayes demonstrated a notable accuracy of 82 %. This signifies a commendable performance in discerning between fresh and chemically adulterated fruits.

4.2. Deep learning model evaluation

The previously developed "DurbeenNet" model demonstrated promising results in image analysis tasks, indicating its potential in the field. However, subsequent evaluations revealed that it was outperformed by a newly proposed hybrid model. This hybrid model achieved a higher accuracy rate of 97.03 %, showcasing its improved performance and effectiveness compared to the initial "DurbeenNet" model.

4.3. Hybrid model evaluation

The newly introduced "SensorNet" model, integrating sensor data from both a Formaldehyde Detection Sensor and previously captured images, achieved the highest accuracy at 97.03 %. This substantial improvement over "DurbeenNet" emphasizes the effectiveness of combining deep learning with chemical sensors for enhanced fruit contamination detection. Table 1 exhibits the comparative analysis of the accuracy of each machine learning deep learning along with the proposed hybrid model.

Table 1 outlines the performance metrics of various machine learning and image classification models, including a sensor-based hybrid model. For deep learning and hybrid architectures, it presents accuracy percentages and loss percentages across folds, reflecting the models' predictive accuracy and deviation from actual labels. The "Average Accuracy" column aggregates the overall performance of each model across all folds. Notably, the "Proposed Model" consistently outperforms its counterparts, achieving the highest average accuracy of 97.03 % while also having a smaller parameter count. In contrast, previously proposed models like "DubeenNet" demonstrate slightly lower average accuracies, suggesting differences in their suitability for the dataset. This concise presentation of performance metrics facilitates model selection and evaluation, with the novel proposed model demonstrating superior accuracy in detecting chemical-mixed fruit compared to other models.

Table 1
Comparative analysis of the proposed hybrid model with other machine learning and deep learning models.

Architecture	Classifier/Model	Accuracy
Machine Learning	Decision Tree	81 %
	Naïve Bayes	82 %
Deep Learning	DurbeenNet	96.71 %
Hybrid	SensorNet	97.03 %

4.4. Confusion matrix

In the context of multi-class classification with eight classes (fresh_apple, mixed_apple, fresh_malta, mixed_malta, fresh_mango, mixed_mango, fresh_banana, and mixed_banana), a categorical classification confusion matrix serves as a tool to assess a machine learning model's performance. It organizes the model's predictions and actual class labels into a grid, allowing for the calculation of various performance metrics for each class. The confusion matrix illustrates the relationships between predicted and actual classes, with the vertical axis representing the true class and the horizontal axis representing the predicted class. Fig. 8 depicts the confusion matrix for all classes of the hybrid model, providing an evaluation of each class's performance. On the vertical axis, the actual class is indicated as "True Level," while the horizontal axis represents the predicted class, labeled as "Predicted Level" by our model.

4.5. Discussion

The graph depicted in Fig. 9 illustrates the training and validation accuracy progression for each fold of the proposed hybrid model over multiple training epochs. Each fold represents a separate evaluation of the model, following the standard practice of cross-validation. The X-axis represents the number of training epochs, showing how the model's accuracy evolves as it learns from the training data. Meanwhile, the Y-axis measures accuracy, indicating the percentage of correct predictions made by the model on the validation dataset.

Fig. 10 presents two separate plots, each providing insights into the training and validation loss across multiple folds for the proposed model. In the following graph, X-axis represents the training epochs, depicting the model's loss, indicating errors during training, changes over time. Each line on the graph, distinguished by a unique color and labeled with a fold number in the legend, corresponds to a different model evaluation. Similarly, the "Validation Loss for Each Fold" graph illustrates the model's performance on a separate validation dataset. It mirrors the structure of the training loss graph, enabling a comparative analysis of loss trends across folds. These plots assist in evaluating the model's convergence, potential overfitting, and overall performance for each fold, providing valuable insights into its training dynamics and predictive capabilities.

In Fig. 11. The accuracy of applied each machine learning, deep learning and hybrid model is compared. It shows that the hybrid model

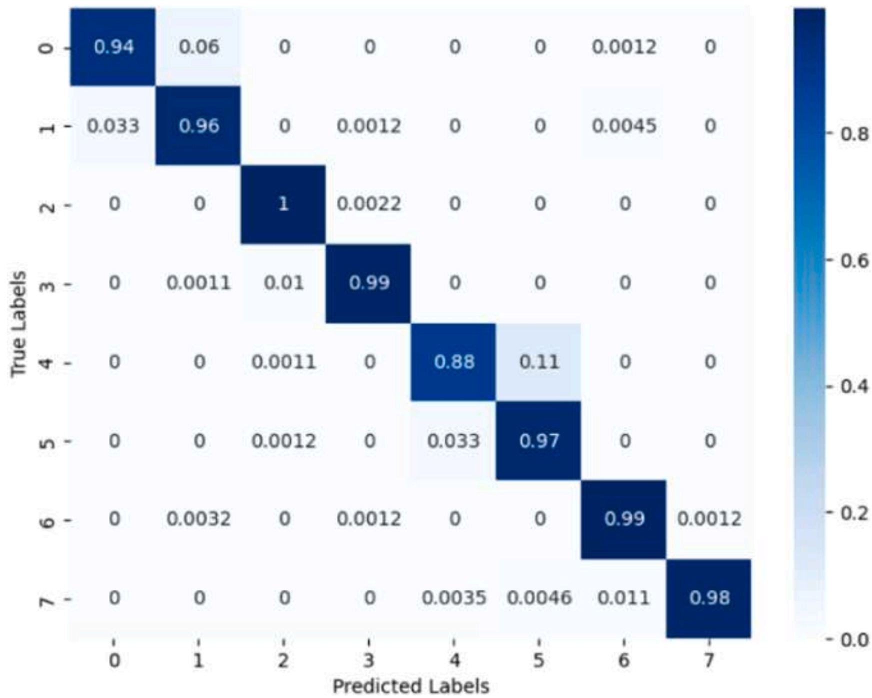

Fig. 8. Confusion matrix of the hybrid model.

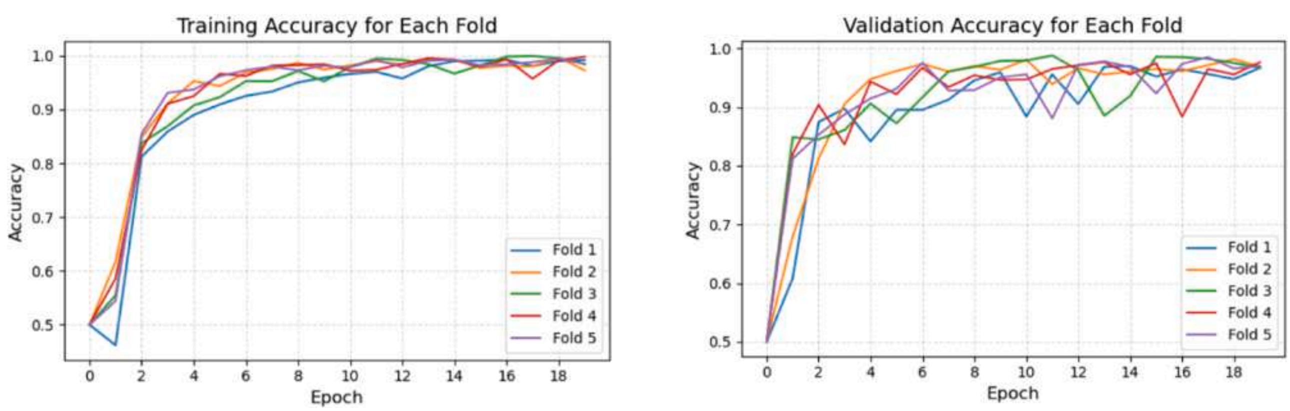

Fig. 9. Training and validation accuracy of the hybrid model.

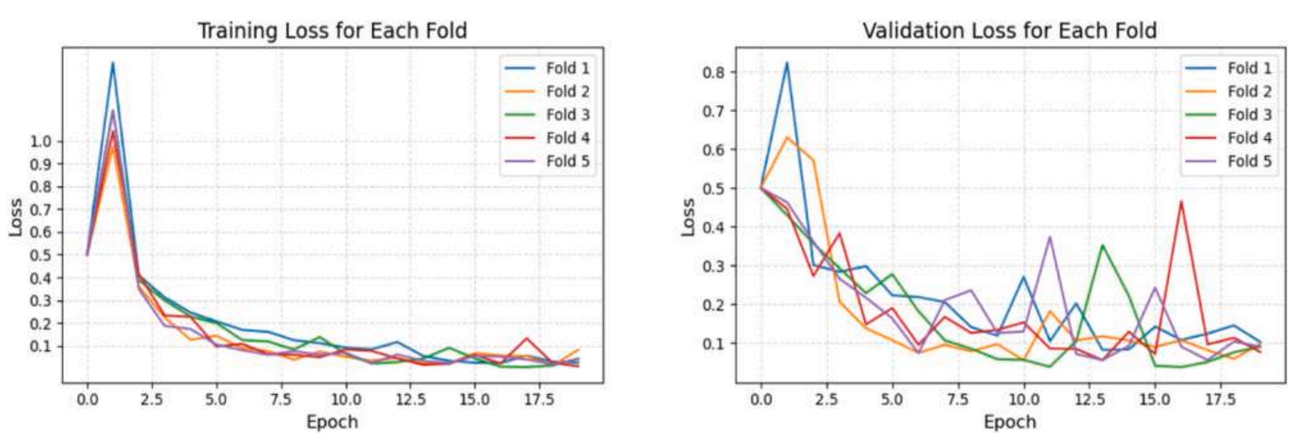

Fig. 10. Training and validation loss of the hybrid model.

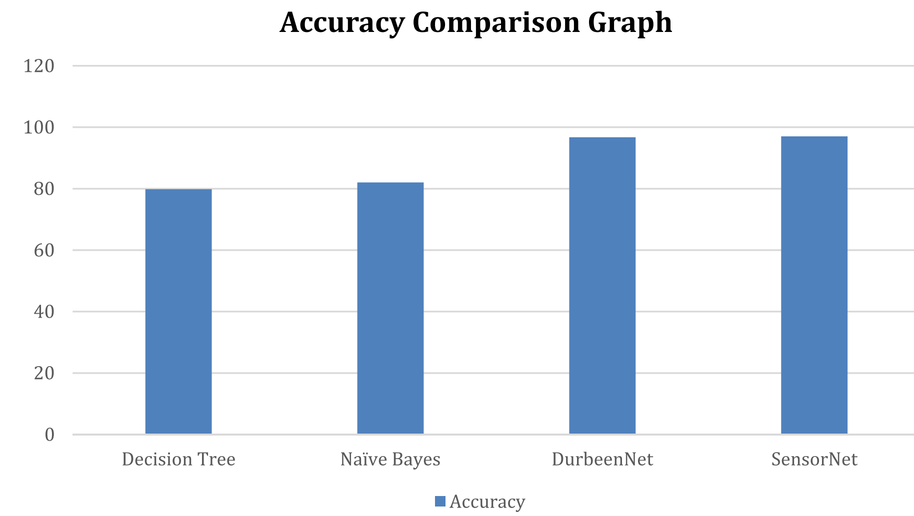

Fig. 11. Accuracy comparison graph for all applied models.

"SensorNet" outperforms all the other model by achieving 97.03 % accuracy. Whereas, the deep learning model "DurbeenNet" model attained 96.71 % accuracy. From two of the applied machine learning algorithms Decision Tree and Naïve Bayes, we have got the accuracy of 79.83 % and 82.0 % respectively.

5. Conclusion

In conclusion, the introduction of the "SensorNet" model marks a significant advancement in fruit contamination detection, as evidenced by its remarkable accuracy of 97.03 %. By leveraging sensor data from both a Formaldehyde Detection Sensor and previously captured images data, this hybrid approach demonstrates the power of combining deep learning with chemical sensors. With the help of this hybrid model can detect toxic substances in fruits more accurately. By providing such a booming framework for detection and identification, the proposed "SensorNet" model offers a promising solution to ensure the safety and integrity of fruits consumed by the general public. Overall, the findings underscore the efficacy of the proposed model in accurately identifying chemical-mixed fruit, positioning it as a promising tool for ensuring food safety and quality.

5.1. Limitation

While the hybrid "SensorNet" model demonstrates remarkable capabilities in detecting chemical adulteration in fruits through the integration of sensor and image data, it is important to acknowledge its limitations. One significant constraint is its inability to detect other chemical elements present in fruits beyond formaldehyde. The model's reliance on sensor data specifically tailored for formaldehyde detection restricts its applicability to identifying this particular toxic substance. Consequently, it may overlook the presence of other harmful additives or contaminants that could compromise fruit safety. This limitation underscores the need for further research and development to broaden the model's scope, encompassing a wider range of chemical pollutants commonly found in fruits. Additionally, ongoing advancements in sensor technology and machine learning algorithms may facilitate the expansion of the model's capabilities to address this limitation in the future. Nonetheless, it is crucial for users to be mindful of this constraint when interpreting the results provided by the "SensorNet" model and to supplement its findings with other analytical methods where necessary.

5.2. Potential impact

Beyond the study's specific focus on formaldehyde detection in certain fruits, the "SensorNet" method carries broader implications for public health and food safety. By integrating sensor and image data, it offers a versatile approach applicable to identifying various contaminants in different foods. This technology has the potential to revolutionize food safety practices by enabling rapid and reliable detection of pesticides, heavy metals, and pathogens throughout the food supply chain. The method's scalability and affordability could democratize food safety monitoring, empowering consumers and regulatory agencies to make informed decisions and take proactive measures to mitigate risks. In essence, the "SensorNet" method represents a pivotal advancement with far-reaching impacts on global food security and public health.

5.3. Future prospects

The promising results of the "SensorNet" model in detecting formaldehyde contamination in fruits pave the way for future enhancements and broader applications. Future research should focus on expanding the range of detectable chemical substances by integrating additional sensors capable of identifying various contaminants such as pesticides, heavy metals, and other hazardous chemicals. Advances in sensor technology, deep learning models and "Deep Recurrent Graph Convolutional Architecture for Sensor Fault Detection" (Darvishi et al., 2023) could further improve the model's validity and reliability. Additionally, developing portable, user-friendly devices based on the "SensorNet" model could empower consumers to test food safety at the point of purchase, democratizing food safety monitoring. By addressing its current limitations and leveraging advanced technologies, the "SensorNet" model can evolve into a comprehensive solution for ensuring food safety and quality, contributing significantly to global food security and public health.

CRediT authorship contribution statement

Abdus Sattar: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Md. Asif Mahmud Ridoy:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Aloke Kumar Saha:** Investigation, Methodology, Validation, Visualization, Writing – review & editing. **Hafiz Md. Hasan Babu:** Investigation, Methodology, Validation, Visualization, Writing – review & editing. **Mohammad Nurul Huda:** Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

We confirm that there are no financial or non-financial relationships that could be perceived as potential conflicts of interest. We have followed ethical guidelines, obtained necessary permissions, and ensured participant confidentiality.

Data availability

Data will be made available on request.

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