AirVision

Submitted in partial fulfillment of the requirements
of the course **Innovative Product Development-II**

Year 2, Sem IV Computer Engineering

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CERTIFICATE

This is to certify that the project entitled **“AirVision”** is a bonafide work of **“Aaditya Mehta(60004230005), Ansh Saboo(60004230153), Aryan Sanghani(60004230043), Hardik Iyer(60004230255)”** submitted as a project work for the course **Innovative Product Development-II, Year 2, Semester IV, SY B.Tech Computer Engineering**

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IPD Project Report Approval for BTech Semester IV

This project report entitled “AirVision” by Aaditya Mehta, Ansh Saboo, Aryan Sanghani, Hardik Iyer is approved for the **Innovative Product Development-II, Year 2, Semester IV, SY B.Tech Computer Engineering**

Examiners

1.--

2.--

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included. We have adequately cited and referenced the original sources. We also declare that We have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

Our product features an AQI-predicting machine learning model that delivers accurate forecasts, identifies pollution trends, and aids in policymaking. It empowers individuals to take precautions and supports governments in making informed decisions and reforms to improve air quality, protect public health, and ensure sustainable urban management.

Our research focuses on addressing inconsistencies in government data on waste management, particularly non-biodegradable waste incineration before landfilling. Observed discrepancies include incomplete data on incineration practices, unclear management of organic waste, inaccurate recycling statistics and a lack of transparency in waste segregation. These gaps impede effective AQI management and highlight systemic negligence.

To bridge this gap, we propose a multi-model framework:

1. **Model 1**: Resolves data inconsistencies and accurately quantifies the impact of waste burning on air quality, enabling effective mitigation strategies.
2. **Model 2**: Predicts yearly AQI trends and integrates weather forecasting to anticipate pollution patterns, setting a target for July 21, 2029, in alignment with the Paris Climate Agreement.

Our models aim to empower government agencies to take data-driven actions, including stricter regulations for high-pollution areas, promoting renewable energy, and advancing electric vehicle adoption. Furthermore, public awareness initiatives will encourage responsible waste disposal practices to minimize pollution sources at the grassroots level.

By providing actionable insights into landfill management and non-biodegradable waste disposal, our research aims to mitigate AQI spikes, protect public health, and contribute to a sustainable future. This initiative underscores the critical role of accurate data, predictive modelling, and collaborative efforts in addressing the global air pollution crisis.

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List of Abbreviations

Sr. No.	Abbreviation	Expanded form
i	DSS	Decision Support System
ii	TPD	Tonnes Per Day
iii	SWM	Solid waste management
iv	AQI	Air Quality Index
v	PM	Particulate Matter
vi	CCN	Cloud Condensation Nuclei

1) SURVEY CONDUCTED

1.1) Field Survey

A field survey is a research method where data is collected directly from individuals or groups in a real-world setting to gather insights about their experiences, perceptions, and behaviors. It involves interacting with participants through questionnaires, interviews, or observations to understand their views on a specific topic.

The field survey by IPD Group 38 explored public habits and awareness around waste management and recycling. Through an online form, it gathered information on how people dispose of regular, hazardous, and organic waste, and their recycling practices during festivals. The responses highlighted common behaviors and pointed to areas where more awareness and better waste handling systems are needed.

Fig 1.1.1 How often do you separate recyclables from general waste?

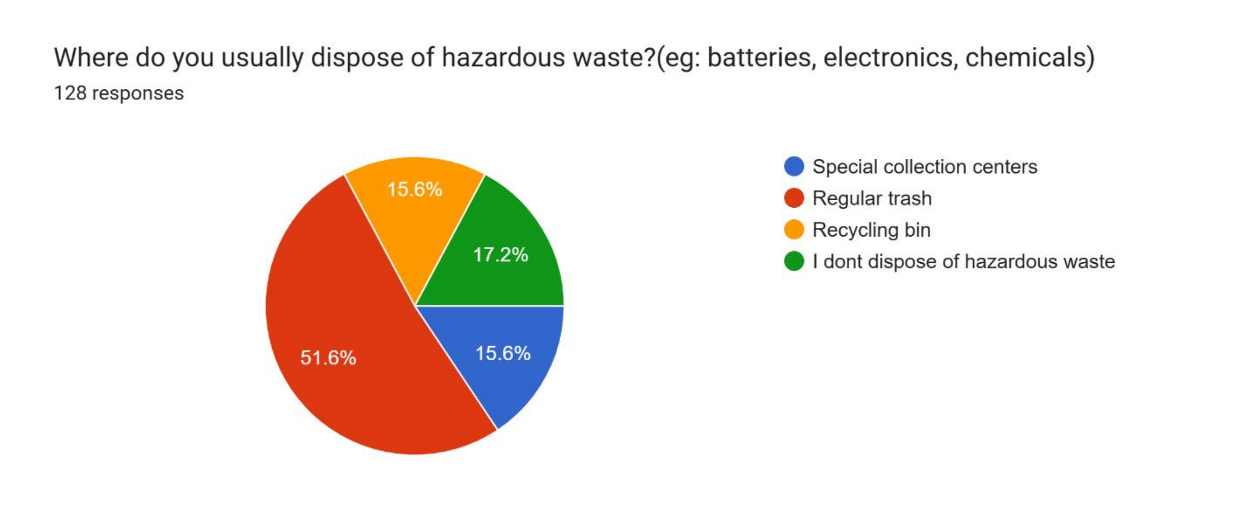

Fig 1.1.2 Where do you usually dispose of hazardous waste?(eg: batteries, electronics, chemicals)

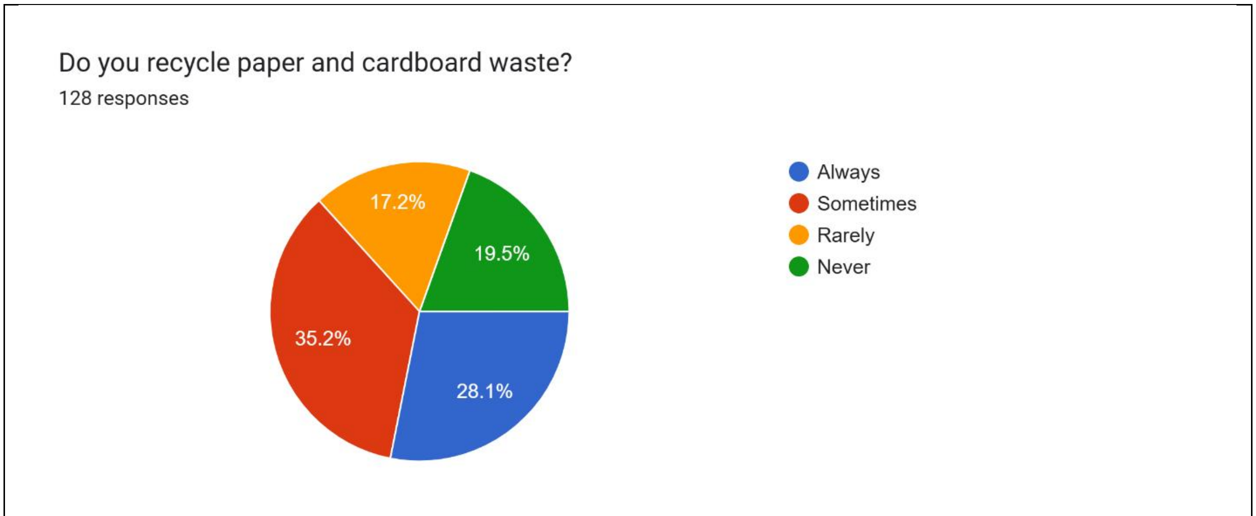

Fig 1.1.3 Do you recycle paper and cardboard waste?

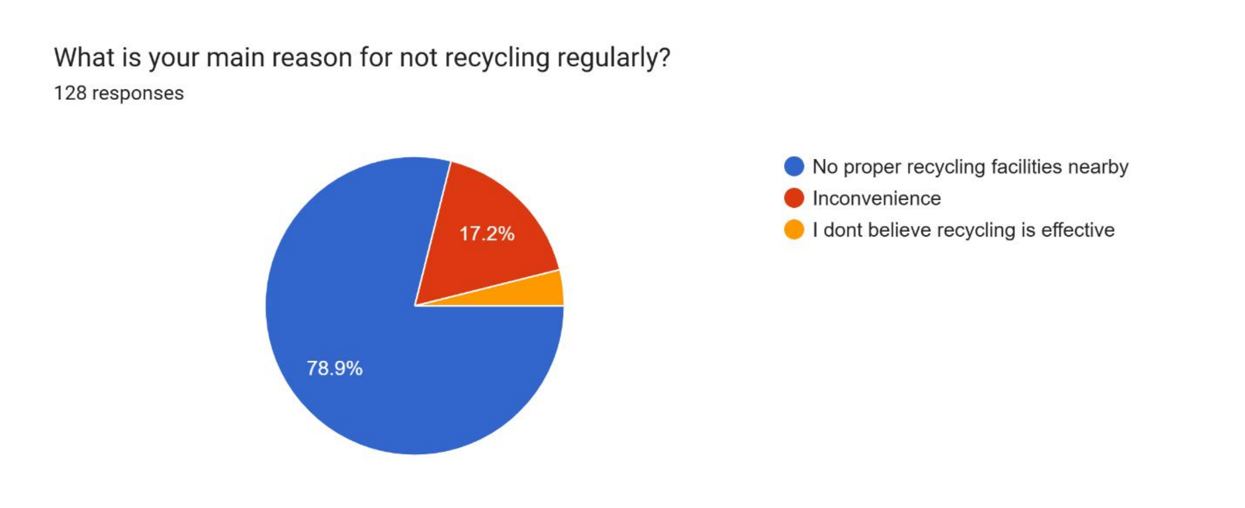

Fig 1.1.4 What is your main reason for not recycling regularly?

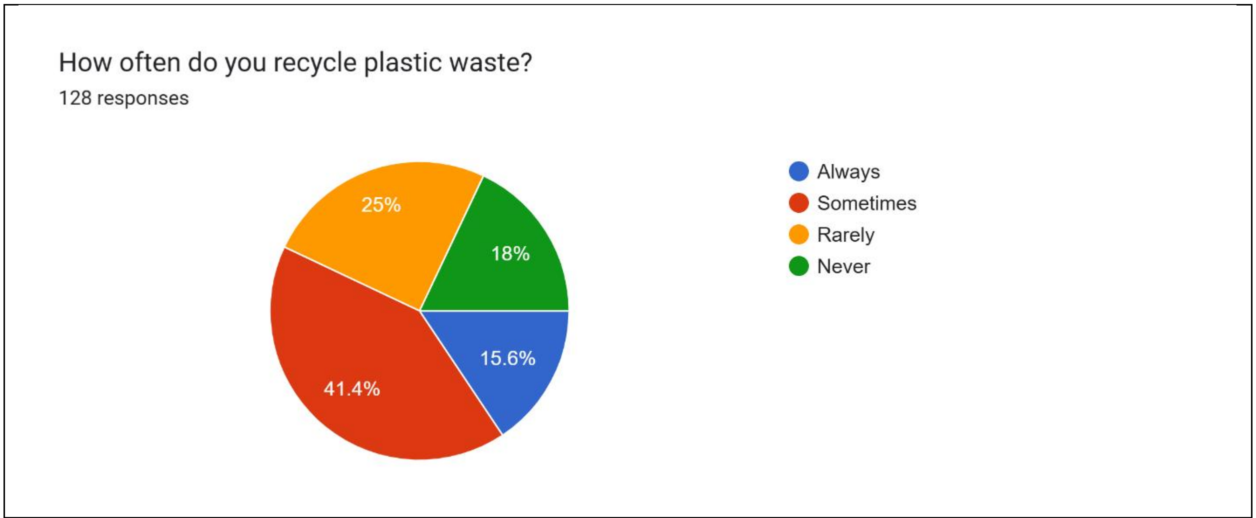

Fig 1.1.5 How often do you recycle plastic waste?

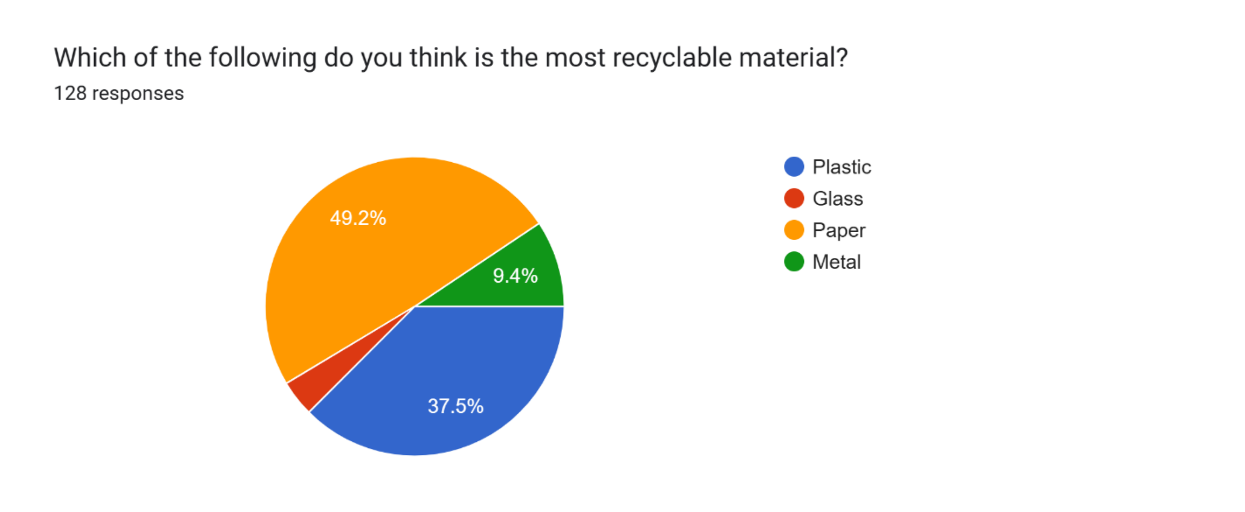

Fig 1.1.6 Which of the following do you think is the most recyclable material?

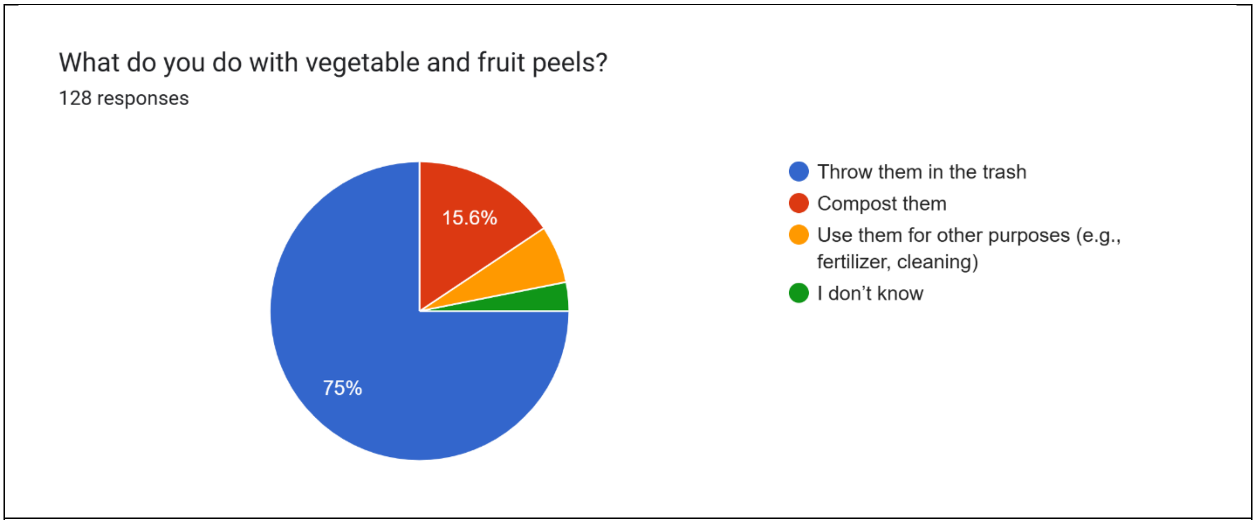

Fig 1.1.7 What do you do with vegetables and fruit peels?

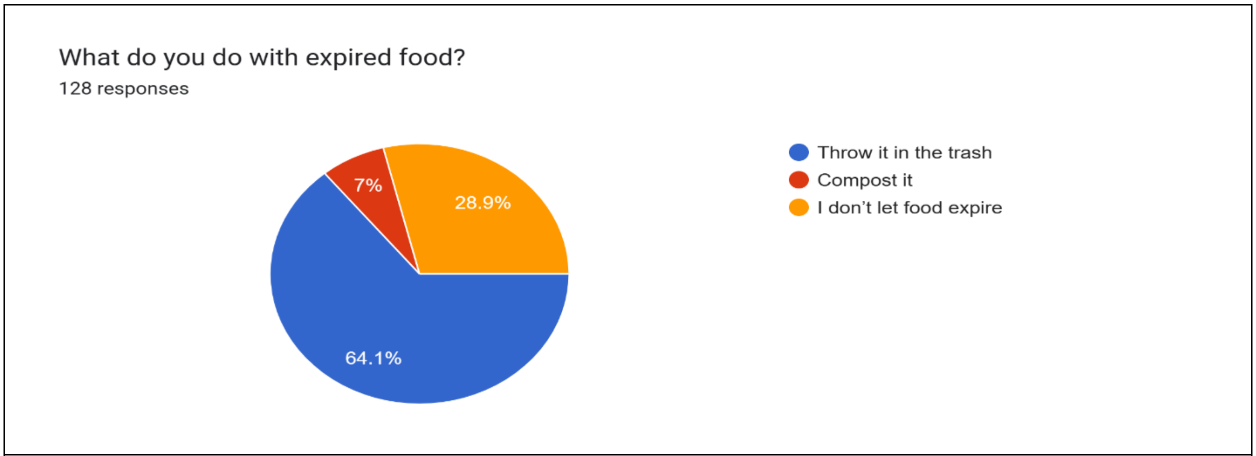

Fig 1.1.8 What do you do with expired food?

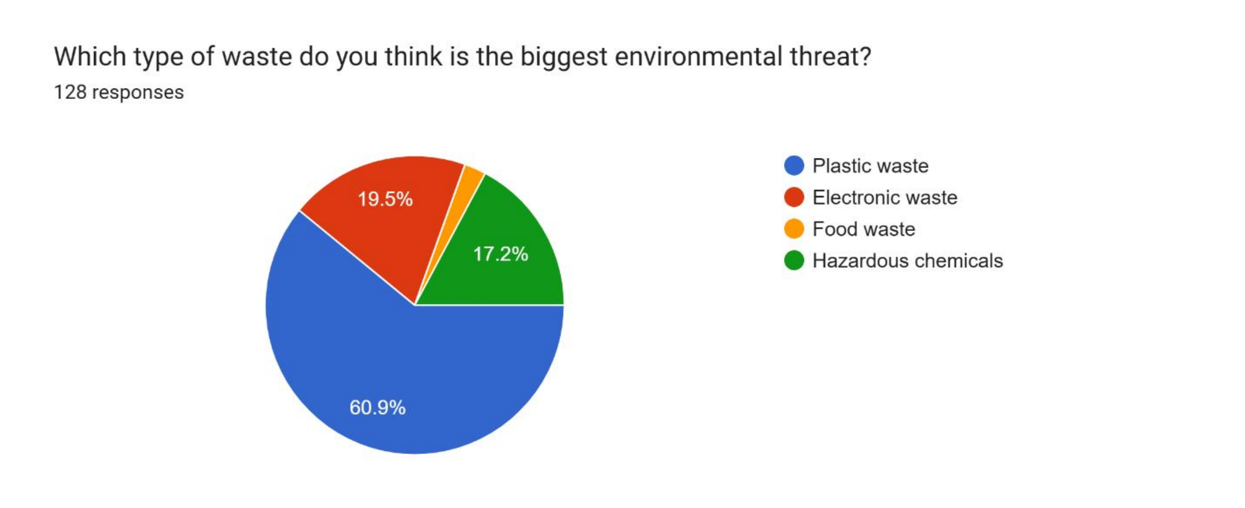

Fig 1.1.9 Which type of waste do you think is the biggest environmental threat?

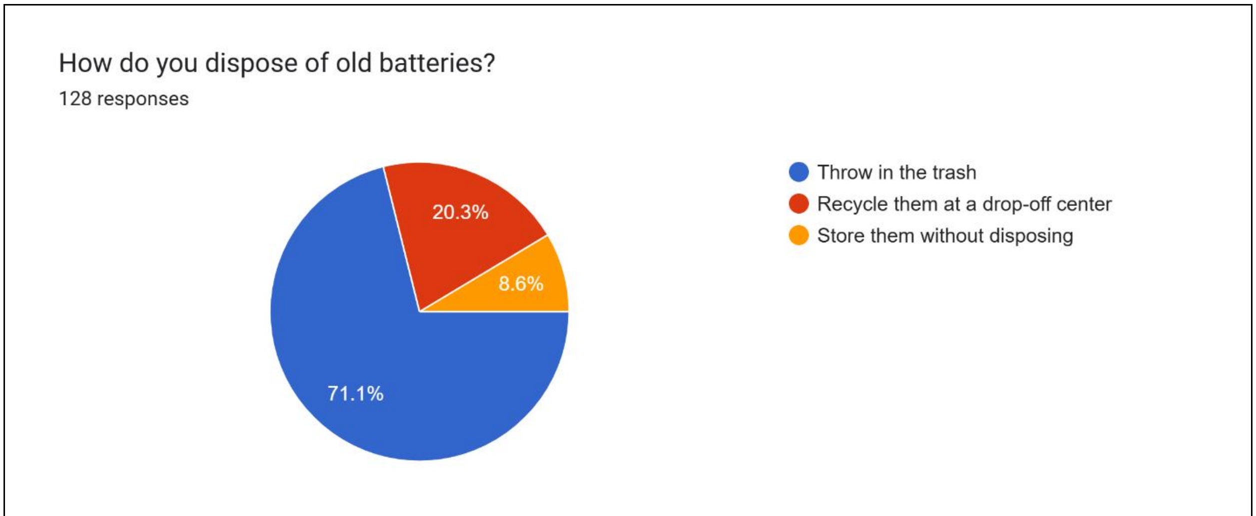

Fig 1.1.10 How do you dispose of old batteries?

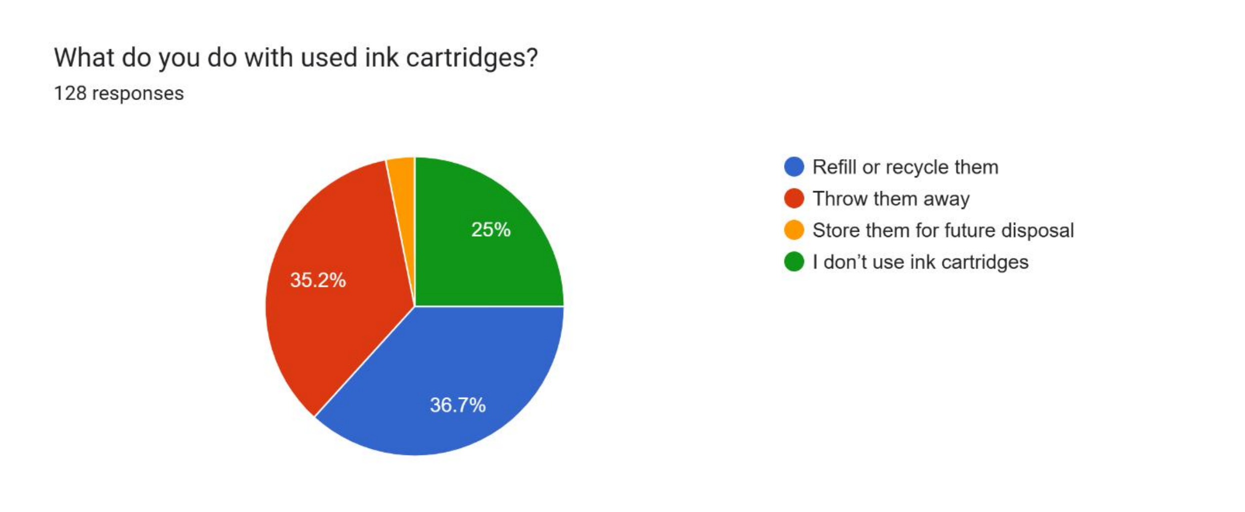

Fig 1.1.11 What do you do with used ink cartridges?

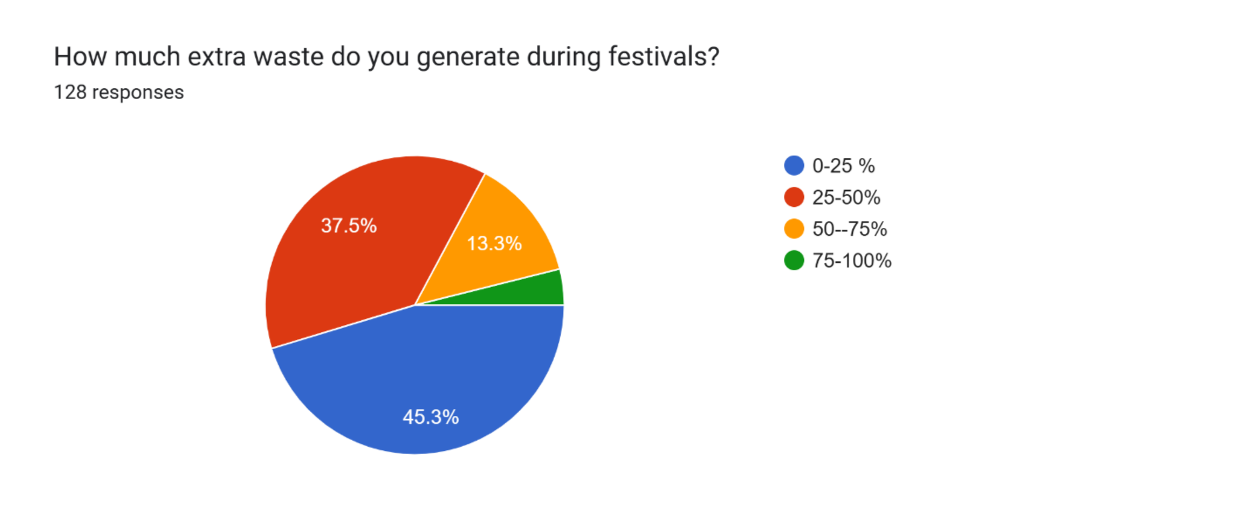

Fig 1.1.12 How much extra waste do you generate during festivals?

1.2) <u>Literature Survey</u>

1)<u>WASTE MANAGEMENT INITIATIVES IN INDIA FOR HUMAN WELL BEING</u>

This paper surveys waste management initiatives in India across five key aspects: waste classification, current practices, policy frameworks, private sector efforts, and future challenges. It highlights major findings, achievements, and gaps, emphasizing the need for sustainable, decentralized, and community-driven waste management solutions for a cleaner and healthier India. It can be broken down into 3 major aspects:

1. **Waste Management Systems and Current Practices:** The paper highlights that waste management in India is primarily handled by municipal bodies, often assisted by the informal sector like rag-pickers. However, waste is largely collected without proper segregation and dumped into landfills, leading to environmental hazards. Observations show that while some cities have begun initiatives like house-to-house collection and private partnerships, overall practices remain outdated and inefficient. Insufficiencies such as lack of segregation at source, inadequate infrastructure, and poor enforcement of existing laws severely hamper progress. Despite these issues, achievements like Delhi's improved waste collection vehicles and certain decentralized models in smaller towns show that gradual improvements are possible.
2. **Government and Private Sector Initiatives:** The literature reveals that the Indian government has developed strong policy frameworks such as the Municipal Solid Waste Management Rules (2000), JNNURM, and the National Urban Sanitation Policy (2008). Private corporations like SPML Enviro, HCL, and Nokia have also introduced successful waste recycling and management programs. While these initiatives demonstrate a growing commitment across sectors, the observation remains that implementation is highly inconsistent, often depending on regional governance quality. Insufficiencies lie in poor coordination among agencies, lack of long-term funding, and superficial partnerships that fail to deliver deep systemic changes. Nevertheless, India's increasing number of pilot projects, public-private partnerships, and international collaborations reflect positive momentum.

3. **Challenges, Gaps, and Future Suggestions:** Major challenges identified include improper waste segregation, limited public participation, lack of awareness, and the unsuitable application of expensive foreign technologies. The paper observes that while some cities are emerging as success stories, most regions still struggle with basic waste handling and recycling. Insufficiencies in training, integration of informal workers, and adapting strategies to local conditions are persistent barriers. Achievements are visible where community-driven and decentralized waste management models have been implemented, as seen in towns like Suryapet and Vellore. The future roadmap suggested involves political will, citizen engagement, region-specific solutions, strengthening of public-private-community partnerships, and building formal recognition for the informal sector.

2) <u>CHALLENGES OF URBAN WASTE MANAGEMENT IN URBAN INDIA</u>

The rapid pace of urbanisation and economic expansion in India has precipitated a significant escalation in the generation of solid waste, exerting immense pressure on already strained waste management infrastructures. Despite numerous policy interventions and regulatory frameworks, effective solid waste management remains an elusive goal for many urban local bodies, revealing critical deficiencies in planning, financing, and implementation. This paper offers a comprehensive examination of the challenges confronting solid waste management in urban India, analysing the interplay between socio-economic dynamics, institutional capacities, technological gaps, and environmental imperatives. It argues that addressing these challenges requires a paradigm shift towards decentralised systems, robust financial models, community participation, and the integration of innovative, sustainable technologies, thereby repositioning waste as a valuable resource for achieving both environmental sustainability and economic development. It can be broken down into 3 major aspects:

1. **Waste Generation and Urbanisation Dynamics:** Several studies, including Robinson (1986) and Meena et al. (2023), establish a strong correlation between urbanisation, rising incomes, and the increasing volume of municipal solid waste (MSW). Urban residents tend to produce nearly double the waste compared to their rural counterparts, resulting in higher per capita waste outputs in cities. This is further aggravated by lifestyle changes, increased resource consumption, and insufficient adaptation of waste management systems.

2. The Central Pollution Control Board (CPCB) (2020-21) highlights that India generates approximately 160,038 tons of solid waste per day, with a significant portion remaining untreated or improperly disposed of, leading to environmental and public health risks.
3. **Implementation Challenges and Regulatory Frameworks:** The regulatory framework for SWM in India evolved with the introduction of the Solid Waste Management Rules (2000 and 2016), shifting from a centralised model to a decentralised approach. However, as Ganesan (2017) and Iyer (2016) point out, substantial implementation gaps persist due to socio-economic disparities, lack of public awareness, administrative inefficiencies, and insufficient infrastructure. Waste segregation at source remains poor, with full segregation achieved in only a small fraction of municipal wards (e.g., 12 out of 250 in Delhi). Moreover, challenges like improper landfill management, financial constraints at the municipal level, and social inequities further hamper the successful execution of sustainable waste management strategies.
4. **Technological and Financial Innovations for Sustainable Management:** Recent literature emphasises the potential of technological and financial interventions to overcome systemic inefficiencies. Sharholy et al. (2008) and Annepu (2012) advocate for innovations such as Waste-to-Energy (WTE) technologies, composting, decentralised processing units, and better landfill designs. Financial mechanisms like result-based financing (The World Bank, 2014), carbon credits, and dedicated tariffs for SWM services are explored as means to enhance municipal capacities and attract private investments. Case studies from cities like Mysuru, Trichy, and international examples such as Yokohama and Mandaue City show that community engagement, technological upgrading, and financial restructuring can significantly improve waste management outcomes when adapted thoughtfully to local conditions.

1.3) **Outcome of survey**

Solid waste management (SWM) in urban India has become a complex challenge, deeply intertwined with the country's rapid urbanisation, socio-economic transitions, technological adoption, and policy implementation gaps. A detailed review of the literature reveals that while frameworks and initiatives exist, there is a pressing need for systematic reforms at operational, financial, technological, and community levels. This section summarises the key outcomes of the survey across ten crucial aspects, offering a comprehensive view of the status, gaps, and future directions in urban waste management.

The following key outcomes were derived from the survey:

1) Need for Behavioural Change and Public Participation:

Public attitude towards waste segregation and responsible disposal remains a major barrier. Awareness campaigns alone have proven insufficient; sustained behavioural nudges, incentivised recycling, school-based education programs, and strict penalties for non-compliance are necessary to instil long-term change.

2) Lack of Waste Segregation Culture:

Despite laws promoting segregation of waste at the household level, in most cities, garbage is still collected and dumped as a mixed mess. This not only makes recycling and composting harder but also increases landfill dependency. In places where awareness drives and small penalties were introduced, better habits took root, showing that change is possible with persistent efforts.

3) Cash-Strapped Municipalities:

Money remains a big bottleneck. Most municipal corporations barely scrape together enough budget for basic garbage collection, let alone advanced treatment or recycling technologies. Much of the spending goes to collection and transport, with very little for actual processing. Cities must innovate with new financing models like waste user fees, PPPs, and tapping carbon markets if they are to upgrade their systems meaningfully.

4)<u>Decentralized Systems Work Better:</u>

Smaller, localised waste management units — like neighbourhood composting pits and ward-level recycling centres — are more efficient, cheaper, and more participatory than massive centralised plants. Success stories from Mysuru, Ambikapur, and even global examples like Yokohama show that when communities own their waste solutions, results improve dramatically.

5) <u>The Untapped Potential of Organic Waste:</u>

Organic waste — food scraps, garden waste, biomass — forms a huge portion of India's municipal solid waste, yet only a small fraction is composted. Properly managed, this waste could become a rich resource for compost, biogas, and even electricity. Cities like Mysuru have shown that simple home composting initiatives or community biogas plants can drastically reduce landfill loads and improve soil health, especially crucial for urban agriculture.

6)<u>Willingness to Pay (But Only for Good Services):</u>

Interestingly, around 60% of survey respondents indicated they would be willing to pay a small monthly fee (Rs 50–100) for better waste management services — **if** they see visible improvements. People want proof of action — like clean streets, regular pickups, and efficient segregation — before they accept user fees. This shows potential for financing improvements if trust is built first.

7) <u>High Awareness but Low Daily Practice:</u>

Most urban citizens are aware that waste segregation and responsible disposal are important, but less than half actually practice it consistently at home or work. While 80–90% of respondents agreed that waste segregation should be mandatory, only around 40% said they segregate dry and wet waste daily. This highlights the gap between knowledge and behavior that needs to be bridged through persistent nudging and incentives.

The challenges of solid waste management in urban India are deeply rooted in the rapid pace of urbanization, institutional inefficiencies, financial constraints, and a gap between public awareness and actual behavior. While regulatory reforms, technological innovations, and decentralized models show promise, effective implementation demands greater citizen participation, stronger municipal capacity, and strategic financing mechanisms. Survey outcomes highlight that although there is growing public awareness and willingness to engage, practical execution and trust in systems remain critical barriers. Moving forward, a shift towards viewing waste as a resource, integrating informal sectors, embracing smart technologies, and positioning waste management as a climate action strategy will be essential. Only a collaborative, inclusive, and future-oriented approach can help India turn its urban waste crisis into an opportunity for sustainable growth and resilience.

2)NEED OF THE PRODUCT

The Air Quality Index (AQI) is a standardized system used to measure and report air quality in a specific location. It provides a numerical value that represents the concentration of pollutants in the air and translates this data into categories that indicate the level of health concern. The AQI helps individuals understand the quality of the air they breathe and take precautions when necessary.

It tracks pollutants like PM2.5, PM10, Ozone (O_3), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Carbon Monoxide (CO). Ranging from 0 to 500, the AQI is categorized into levels like Good, Moderate, Unhealthy, and Hazardous, helping individuals understand pollution risks.

As of December 1,2024, New Delhi is the 6^{th} most polluted city on earth.

Air pollution is linked to a range of serious health problems-

Respiratory diseases like asthma, chronic bronchitis, and chronic obstructive pulmonary disease (COPD), as fine particles (PM2.5) irritate the lungs, making it difficult to breathe.

Cardiovascular diseases such as heart disease, stroke, and hypertension, by causing inflammation and narrowing of blood vessels.

Long-term exposure to harmful substances like benzene and formaldehyde is associated with an increased risk of cancers, particularly lung and bladder cancer.

Additionally, air pollution can cause neurological diseases, contributing to cognitive decline and neurological disorders such as Alzheimer's and Parkinson’s disease.

Pregnant women exposed to polluted air are at a higher risk of premature births, low birth weight, and developmental problems in children.

Addressing these health impacts requires reducing air pollution through government policies, public awareness, and individual actions to minimize exposure.

The most popular causes of an increased AQI levels are-

- Vehicular emissions are a major contributor, with the increasing number of vehicles releasing pollutants like nitrogen oxides (NOx), carbon monoxide (CO), and particulate matter (PM2.5 and PM10). Industries emit sulphur dioxide (SO_2), VOCs, and other harmful chemicals, often bypassing emission norms.

- Dust from rampant construction and poorly maintained roads adds to particulate pollution.
- Agricultural stubble burning, especially in northern states, worsens air quality during winter, when temperature inversion traps pollutants near the ground.
- Coal-fired power plants are another significant source, emitting large quantities of PM, SO_2, and NOx.

There are no articles or reports or papers discussing the AQI spikes caused by landfill incinerations because there are no consistent datasets which explore it.

Upon deeper exploration, we examined government sites and research publications, which provided extensive data on state-level waste collection and management.

The reports outlined total solid waste generation, the amount collected, waste recycled, and the portion landfilled.

However, discrepancies in the data which we noticed raised significant concerns.

Observed Inconsistencies:

1. <u>Lack of Data on Incineration Before Landfilling</u>

   There is no clear information on how much waste is incinerated prior to being landfilled.
2. <u>Organic Waste Management</u>

   The data does not clarify how much organic waste is composted or incinerated. If incinerated, organic waste, due to its high calorific value - produces more CO_2 compared to non-biodegradable waste.
3. <u>Accuracy of Recyclable Waste Data</u>

   It is unclear whether the reported quantities of recyclable waste are accurate. If not recycled, is it being incinerated instead?

   With the most important point being-
4. <u>Transparency in Waste Segregation and Incineration</u>

   The reports <u>do not</u> disclose the amount of waste incinerated before landfilling or the criteria used to segregate waste for incineration. This highlights significant negligence in waste management practices.

These gaps indicate a lack of transparency and efficiency, emphasizing the need for stricter data monitoring and sustainable waste management reforms.

To address these inconsistencies, our product focuses on-

- Predicting the amount of non-biodegradable waste sent to each landfill. This allows us to estimate the incineration required and identify spikes in AQI caused by landfill burning.
- These findings highlight lapses in management responsibility, negligence at the ground level, and insufficient government oversight.
- Our product will also assist governments in identifying necessary reforms to improve waste management and reduce AQI spikes. With less than five years remaining on the climate clock, it is imperative for governments worldwide to take decisive action to combat climate change.

The direct correlation between AQI peaks and climate change is-

Reduction in Solar Radiation (Dimming Effect)

- High levels of particulate matter (PM2.5 and PM10) scatter and absorb sunlight, reducing the amount of solar radiation that reaches the Earth's surface.
- This "dimming" effect can lower daytime temperatures and impact weather patterns.

Cloud Formation and Rainfall Patterns

- Particulates in the air, especially aerosols, act as cloud condensation nuclei (CCN).
- Higher concentrations of pollutants can lead to the formation of smaller water droplets in clouds, making them less likely to coalesce into rain. This can suppress precipitation in polluted regions.

Heat Island Effect

- Urban areas with poor air quality often experience the "urban heat island effect," where pollutants trap heat, raising local temperatures.
- This localized warming can alter wind patterns and humidity levels, influencing weather in and around cities.

Impact on Monsoons

- Aerosols from pollution can alter monsoon dynamics by disrupting atmospheric circulation and reducing the temperature gradient critical for monsoon systems.
-

3)PROBLEM FORMULATION

3.1) Problem Formulation:

The most important of the many features that our product offers is an AQI predicting machine learning (ML) model that addresses key challenges related to air quality monitoring, health protection, and urban management. It provides real-time and accurate AQI forecasts, helping individuals, especially vulnerable populations, take precautions against harmful air. By analyzing historical data, it can identify pollution trends and predict future levels, aiding in pollution control and disaster preparedness.

Overall, it supports government bodies in making informed decisions to protect public health and improve air quality and to make informed reforms for the betterment of the air quality.

The model also helps bridge gaps in monitoring infrastructure, particularly in regions where real-time AQI monitoring stations are sparse. By analyzing data from nearby locations and extrapolating trends, the ML model can provide forecasts for areas with limited resources. This predictive capability is invaluable during critical periods, such as the onset of winter smog or during wildfire seasons, where air quality can rapidly deteriorate, posing significant risks to public health.

What is it that we are trying to solve?

The main problem that we are trying to solve is that our Model 1 will segregate the inconsistencies of the government data about burning non-biodegradable waste and how it affects the AQI (Air Quality Index).

The most critical challenge lies in accurately managing and improving air quality and relieving the inconsistencies of data concerning the burning of non-biodegradable waste which will be taken care Model 2.

Data collected by government agencies on the scale, frequency, and intensity of waste burning do lack uniformity, timeliness, and accuracy. This inconsistency hampers the ability to assess its true impact on the Air Quality Index (AQI) and, consequently, on public health and the environment. We also aim at creating an awareness among the general population regarding the effect of improper disposal of their waste products.

Model 3 aims to predict the AQI levels on a yearly basis and we would like to ideally set the ultimate date to 21st July, 2029 at 12 noon as per Paris Climate agreement. This model also aims to predict weather.

3.2) Product objectives

We aim to successfully implement three ML models-

The first model aims at correctly predicting the total estimated quantity of non-biodegradable waste at the landfill level. Keeping in mind the necessary pivots for example- natural disasters, major public events, etc. Starting at housing level, we build up our dataset onto locality and then entire districts specific to a dumping ground.

Our second machine learning model would predict the Air Quality Index (AQI) based on the impact of landfill burning on pollution levels. It would take in data such as the amount of biodegradable waste, amount of misdiagnosed organic wastes and historical AQI levels to forecast the current air quality. By analyzing the relationship between landfill burning and pollutants like PM2.5, CO, and NOx, the model would generate real-time AQI predictions, alerting individuals and authorities about potential air quality hazards. This would allow for timely interventions and health precautions, particularly in areas near landfill sites.

The third model also leverages the data of our Model 2, historical AQI data and pollutant concentration trends to establish baseline conditions and identify seasonal patterns, such as increased pollution during dry spells or winter months. Urban proximity and population density near landfill sites are crucial factors, as they indicate the scale of potential human exposure to deteriorating air quality. Furthermore, landfill-specific characteristics, such as size, capacity, methane gas emissions, and waste composition, are included to account for the varying nature of fires and their pollution profiles.

Overall, the model bridges critical gaps in understanding and managing the relationship between landfill fires and air quality, fostering a more proactive and sustainable approach to pollution control. Our machine learning model addresses the critical challenge of predicting the Air Quality Index (AQI) by analyzing the significant impact of landfill burning on pollution levels. By integrating diverse data sources, including fire intensity, waste composition, meteorological conditions, and historical pollutant trends, the model provides accurate, real-time AQI forecasts. This empowers individuals to take timely precautions and aids policymakers in implementing targeted interventions for air quality management. With its ability to enhance public awareness and drive sustainable practices, the model offers a proactive solution to mitigating the harmful effects of landfill fires on the environment and public health.

3.3) Applications of the product

The Air Quality Index (AQI) predicting machine learning model serves as a vital tool for addressing air pollution challenges. Its ability to provide accurate, real-time forecasts and actionable insights has a profound impact on various aspects of society, including public health, environmental management, urban planning, and policymaking.

By integrating diverse data, such as waste composition, weather conditions, and historical pollution trends, the model enhances our understanding of pollution dynamics and equips stakeholders with the tools needed to mitigate its adverse effects.

Where will it be used?

1) Schools and Hospitals:

Sensitive locations where timely air quality data can prevent exposure to harmful pollutants.

2) Waste Disposal Sites and Landfills:

Landfill sites, especially those located in or near populated areas, can benefit greatly from the model. By predicting AQI levels in real-time, authorities can monitor the impact of landfill burning and take swift action to control fires. The model can also help assess the effectiveness of waste management practices and suggest areas for improvement to minimize burning events.

3) Emergency and Disaster Response Centers

In regions prone to large-scale landfill fires or other air quality crises, emergency response centers can use the model to receive early warnings about deteriorating air quality. This would allow them to deploy resources such as firefighting units, medical teams, and air filtration systems to affected areas quickly, minimizing health risks for the population.

4)Agricultural Areas (Stubble Burning):

In agricultural regions where open burning of crop residue is common, such as in parts of India, China, and other developing countries, the AQI prediction model can provide early warnings of increasing pollution levels due to stubble burning. This would allow farmers, local governments, and environmental groups to coordinate better solutions to reduce burning and manage air quality during peak burning seasons.

The main goal of our model being-

5) After the model comes up with the inconsistencies in the actual data and calculate data, the respective authorities can then initiate changes at the landfill messages to overcome the negligence caused.

6) Helping government agencies take calculated actions in the present to safeguard the future-

1. With precise AQI predictions, authorities can identify regions or time periods likely to experience severe air quality deterioration. Policies such as stricter emission standards for industries, phasing out older vehicles, or regulating construction activities in high-risk areas can be implemented well in advance, reducing pollution sources and mitigating their long-term impact.

2. Investment in Renewable Energy and Technology

Anticipated AQI trends can justify increased investment in clean energy technologies like solar and wind power, reducing dependence on fossil fuels. Additionally, policies promoting electric vehicles (EVs) and waste-to-energy plants can be fast-tracked, addressing key sources of air pollution.

3. Health Advisory and Preparedness

Policy frameworks for public health can be strengthened using AQI forecasts. Governments can allocate resources for healthcare infrastructure, plan vaccination drives for respiratory diseases, and launch awareness campaigns about protective measures like air filters and masks, especially for vulnerable populations.

4. International Commitments and Climate Action

Forecasting AQI helps align domestic policies with global environmental goals, such as commitments under the Paris Agreement. Governments can prioritize reducing specific pollutants linked to AQI degradation, ensuring compliance with international benchmarks while improving air quality locally.

5. Enhancing Public Awareness

Using forecast data, governments can engage in transparent communication with citizens about air quality challenges and solutions. Campaigns encouraging reduced personal vehicle use, proper waste management, and energy-efficient practices can gain traction when backed by data-driven projections.

By taking calculated actions based on AQI forecasts, governments can not only mitigate immediate environmental risks but also lay the foundation for a healthier, more sustainable future.

<u>How is it useful to society?</u>

1. Reducing Public Health Risks

The model predicts the impact of incineration on air quality, identifying when AQI levels are likely to become hazardous. This information allows authorities to issue timely health advisories, especially for vulnerable populations like children, the elderly, and those with respiratory or cardiovascular conditions. Early warnings can prompt people to take precautions, such as staying indoors or wearing masks, reducing health risks associated with poor air quality.

2. Guiding Waste Management Practices

By analyzing how non-biodegradable waste incineration affects AQI, the model encourages more sustainable waste disposal practices. Governments and waste management agencies can use the insights to promote recycling, reduce incineration rates, or adopt cleaner incineration technologies, ultimately minimizing environmental damage.

3. Supporting Policy Development

The model provides data-driven insights for policymakers, helping them craft regulations to control pollution levels. For instance, it can inform decisions to limit incineration during periods of high pollution or invest in alternative waste processing methods like composting or waste-to-energy technologies.

4. Promoting Sustainable Urban Development

The model's predictions can inform urban planning decisions, such as zoning regulations to separate residential areas from incineration facilities. This minimizes direct exposure to pollutants and ensures healthier living conditions for communities.

5. Raising Public Awareness

The model's outputs can be used to educate the public about the environmental and health consequences of incineration. Increased awareness can lead to better waste segregation at the source, reducing the volume of non-biodegradable waste that requires incineration.

6. Driving Technological Innovation

The insights provided by the model highlight the need for cleaner and more efficient waste processing technologies. This can drive innovation in fields like advanced incinerators with lower emissions or alternative waste disposal systems that minimize air pollution.

3.4) Novelty

The AQI predicting machine learning model stands out from other air quality prediction tools and systems due to several unique and innovative features that enhance its accuracy, timeliness, and relevance.

In the initial semester, our objective was to predict changes in the Air Quality Index (AQI) resulting from the burning of non-biodegradable waste at dumping grounds. We began by scraping data from various government websites and research papers. However, as we delved deeper, we realized that the available data was inconsistent—each source provided varying figures. This lack of uniformity led us to pivot our approach: instead of relying on external data, we decided to build our own dataset by collecting waste from our own households and scaling it up using statistical and empirical methods to represent dumping grounds.

While developing our models, we encountered further challenges—many government datasets were outdated, with some not updated since 2011. Our first model used linear regression analysis to estimate the generation of non-biodegradable waste at different scales. It started with individual residential complexes and aggregated data to the locality level. However, we soon noticed a limitation: most of our participants shared similar backgrounds in terms of education, urbanization, and population density, which skewed the data and limited its generalizability.

Faced with this obstacle, we decided to shift our focus once again. We began formulating a new equation that could account for a wider range of socio-economic and environmental factors like ward specific data with respect to education indices and built up area, also considering fluctuations with respect to surge in waste during festivals and specifically in the monsoon season . We took it upon ourselves to design a system using raw, ground-level data could be used to estimate the volume of waste ultimately reaching Deonar dumping ground.

The first phase of our revised project now centers on creating an equation to approximate the total amount of waste generated, based on grassroots data collection.

1)Long-Term Trend Analysis and Seasonal Predictive Analytics

While many AQI models focus on immediate or short-term air quality assessments, this model goes a step further by using machine learning techniques to identify long-term pollution trends. By analyzing historical data, the model can detect recurring seasonal variations in air quality, changes in landfill burning practices, and shifts in pollution levels due to weather or urbanization. This allows authorities to make long-term decisions based on predictive insights, such as anticipating pollution spikes during certain times of the year or assessing the impact of improved waste management practices on air quality over time. Additionally, these long-term insights can support policy decisions aimed at reducing pollution sources and improving public health outcomes.

2)Real-Time, Predictive Alerts for Pollution Spikes

While many AQI models focus on historical or current air quality data, this machine learning model takes a predictive approach, offering forecasts of future AQI levels. This is especially useful for areas affected by landfill burning, where pollution levels can fluctuate rapidly depending on fire intensity, weather conditions, and other factors. The model can send real-time alerts to individuals, authorities, and organizations about potential pollution spikes before they occur, providing sufficient time for precautionary measures such as reducing outdoor activities, using air purifiers, or shifting school schedules. This feature helps mitigate the health impact of short-term pollution events and allows for better disaster preparedness.

3.5) Scope of the project

The AQI predicting machine learning model has significant potential for implementation and impact, but its scale and range depend on several factors including domain constraints, application limitations, data availability, and technological requirements. While the project has the ability to forecast air quality based on real-time and predictive data, the extent to which it can be fully realized and its range of applicability are shaped by various challenges that need to be considered during development, deployment, and maintenance.

The scalability of the project depends on various factors such as:

1)Data Availability and Quality

The quality of the AQI predictions is highly dependent on the availability, accuracy, and granularity of the data used to train and feed the model. We aim to build our own dataset from the ground level that is the residential level. Hence, as to have a generalized data of the entire population, all the data will be collected by us and a few trusted testers. Our main objective shall be to avoid as much as discrepancies in the recorded data.

2) Location Constraint

While the model can provide valuable insights into future AQI levels, the effectiveness of interventions based on these predictions depends on the dumping grounds we shall be targeting.

Initially, one of the three dumping grounds shall be targeted namely – Deonar, Mulund and Kanjurmarg. The AQI models shall only help to calculate pollution spikes due to incineration at these sites only.

3) Unexpected constraints

The predictive analysis done by Model 3 shall take into consideration the model data, historic data and obvious future events. However, any unexpected events such as natural disasters shall not be taken into consideration. Any spikes in AQI due to unexpected large scale events shall also not be taken into consideration

4) PROPOSED DESIGN

Our system begins by collecting input from residents of residential complexes to create a reliable dataset for waste analysis.

In Model 1, we have created a formula to calculate total waste generated on a ward wise basis. We have calculated the total waste generated on a ward wise basis considering the population, population density, built up area , education indexes and also considering the fluctuations with respect to surge in waste generation in festivals and in the monsoon season. We have taken a cummulative sum of all the waste generated in every ward and thereby have calculated the total waste accumulated in the deonar landfill on a daily as well as yearly basis.

By compiling data from multiple localities, we estimate district-level waste volumes handled by specific dumping grounds. The model also incorporates adjustments for major events like festivals or public holidays, which often lead to significant increases in waste production.

Model 2 focuses on understanding and predicting the environmental impact of non-biodegradable waste incineration, with a particular emphasis on the Air Quality Index (AQI). Leveraging advanced deep-learning frameworks such as TensorFlow and PyTorch, the model analyzes emissions produced during incineration, identifying key pollutants like carbon monoxide, sulfur dioxide, and nitrogen oxides.

Additionally, it accounts for waste mismanagement, such as organic or recyclable materials being incinerated, ensuring a comprehensive evaluation of elemental emissions. By integrating this data with other sources of air pollution, such as vehicular emissions, industrial activities, and construction sites, the model provides a holistic view of AQI levels in the area.

The model also evaluates the role of landfills, including methane and greenhouse gas contributions, in shaping overall AQI. Temporal and spatial analyses allow the model to identify patterns in AQI spikes, whether due to localized activities or broader trends. These insights help users to take proactive measures, such as optimizing waste disposal methods or implementing air pollution control technologies.

By connecting waste management practices directly to environmental health metrics, Model 2 bridges the gap between operational efficiency and sustainability, offering municipalities and policymakers actionable intelligence to mitigate air pollution and its health impacts.

Our model 3 will handle future analytics and predictions by comparing the calculated data from Model 2, historic data and also the necessary data from upcoming major events. The data calculated will help us to estimate the AQI levels for the next 5 years until Climate Day.

The received data will also help us to do weather analysis and how the AQI levels shall drive the upcoming weather conditions.

Formula:

In the formula we have generated, we have considered various socio-economic and environmental factors to calculate the total waste generated for the deonar landfill on a yearly as well as daily basis. In the formula, the parameters which we have considered are the ward wise population,population density, education indices, built-up area and also the fluctuations with respect to surge in waste during festivals and in the monsoon season specifically. The ward-wise waste which we have collected is then added together and using that we can generate daily and yearly waste generated. The formula is:

$$\text{Total Waste per Year (kg)} =$$

$$P \times W_p \times D_f \times E_f \times U_f \times (1 + S_f + S_m) \times 365$$

Model 1:

The AQI prediction model for non-biodegradable waste incineration relies on technologies that can handle both regression and time-series data. TensorFlow and PyTorch are ideal frameworks for building deep learning models, such as LSTMs or GRUs, which are effective in capturing temporal patterns in pollutant emissions and their effect on AQI. Additionally, Keras, a high-level API for TensorFlow, can simplify model prototyping and experimentation. For pollutant analysis and temporal visualization, Matplotlib and Plotly can provide dynamic, interactive charts that help interpret the relationship between waste incineration and AQI changes. These technologies allow the model to simulate and predict the real-time impact of incineration on air quality, helping mitigate environmental risks.

Model 2:

The long-term AQI forecasting model requires advanced time-series analysis and forecasting frameworks to predict air quality trends over a multi-year horizon. Statsmodels is well-suited for traditional statistical methods like ARIMA, offering robust tools for analyzing historical AQI data and incorporating seasonality and trends. For more complex patterns, Prophet, developed by Facebook, provides an intuitive framework for time-series forecasting, including customizable components for holidays and external regressors. For cutting-edge predictions, deep learning frameworks like PyTorch and TensorFlow enable the development of Transformer-based models or advanced RNNs capable of handling vast amounts of historical and environmental data. Additionally, Pandas is critical for data preparation and preprocessing, while Plotly can be used to visualize predicted AQI trends interactively. These technologies ensure the model can provide precise, actionable insights to guide long-term environmental planning and policymaking.

5) Implementation

<u>5.1) Database design</u>

Due to inconsistencies found across government websites and research papers, we decided to develop our own database by scraping data from a variety of these sources.

To estimate the total annual waste generated (in kilograms) by a given area, we devised a formula that incorporates several key factors: population, population density, education index (to account for reduced rural waste due to practices like burning), urbanization index (measured as built-up area in km²), and seasonal surges caused by festivals and monsoons.

$$\text{Total Waste per Year (kg)} =$$

$$P \times W_p \times D_f \times E_f \times U_f \times (1 + S_f + S_m) \times 365$$

Where:

P = Population of the area (number of people)

W_p = Base per capita daily waste generation (kg/person/day), which can be adjusted based on population density or typical values (0.3 kg/day depending on urbanization and economic status)

D_f = Population density factor (dimensionless), representing how population density influences per capita waste generation; can be modelled as:

$$D_f = 1 + k_d \times \left(\frac{Population\ Density - Density(ref)}{Density(ref)}\right)$$

where k_d is an empirical coefficient (0.3), and Density(ref) is a reference density (10000 persons/km²)

E_f = Education index factor (dimensionless), accounting for rural behaviour of burning waste (less waste collected):

$$E_f = 1 - k_e \times (1 - \text{Education Index})$$

U_f = Urbanization index factor, representing built-up area influence on waste generation:

$$U_f = 1 + k_u \times \left(\frac{BUA(km\string^2)}{Area(km\string^2)}\right)$$

where k_u is a coefficient (0.4), and BUA is the fraction of built-up area

S_f = Surge factor due to festivals (0.20 for 20% increase)

S_m = Surge factor due to monsoon (0.10 for 10% increase)

365 = Number of days in a year to convert daily waste to annual was

5.1.1 Data on government sites regarding the data collected which is given as 4000 Tons/Day

Ward	Population	Wp	Density(persons per sq km)	Df	Area(km2)	Avg Education level(Education Index)	Ef	Urbanization index(BUA km^2)	Uf	Sf	Sm	Days	Total Waste	
A	210926	0.3	16874	1.20622	12.50005926	0.75	0.9	1.85	1.059199719	0.2	0.1	365	34525063.01	
B	199550	0.3	70,264	2.80792	2.840003416	0.7	0.88	1.24	1.174647677	0.2	0.1	365	82448779.33	
C	170100	0.3	95,562	3.56686	1.779996233	0.72	0.888	1.79	1.402248042	0.2	0.1	365	107543869	
D	346700	0.3	43,175	1.99525	8.030110017	0.73	0.892	3.37	1.167868186	0.2	0.1	365	102581091.3	
E	413662	0.3	56500	2.395	7.321451327	0.65	0.86	3.87	1.211433489	0.2	0.1	365	146928702.4	
F/N	698000	0.3	53900	2.317	12.94990724	0.62	0.848	4.62	1.142703725	0.2	0.1	365	223084000.1	
F/S	377873	0.3	27000	1.51	13.9952963	0.68	0.872	3.49	1.099747799	0.2	0.1	365	77891464.01	
G/N	590,609.00	0.3	65,828	2.67484	8.972002795	0.58	0.832	7	1.312081936	0.2	0.1	365	245493288.7	
G/S	377,749.00	0.3	37,775	1.83325	9.999973527	0.6	0.84	5.5	1.220000582	0.2	0.1	365	101023360.8	
H/W	495,000	0.3	42,672	1.98016	11.60011249	0.7	0.88	9	1.310341818	0.2	0.1	365	160890435.5	
H/E	579123	0.3	31,270	1.6381	18.52008315	0.55	0.82	8	1.172785401	0.2	0.1	365	129867685	
M/E	950,000	0.3	29,230	1.5769	32.50085529	0.35	0.74	20	1.246147368	0.2	0.1	365	196646560.4	
M/W	580,000	0.3	29,940	1.5982	19.37207749	0.5	0.8	12	1.24777931	0.2	0.1	365	131717766.7	
N	660000	0.3	25,423	1.46269	25.96074421	0.55	0.82	15	1.231118182	0.2	0.1	365	138729013.1	
K/E	1400000	0.3	92000	3.46	15.2173913	0.6	0.84	14	1.368	0.2	0.1	365	792368111.8	
K/W	750000	0.3	29956	1.59868	25.03672052	0.65	0.86	12	1.1917184	0.2	0.1	365	174925197.5	
S	800000	0.3	21164	1.33492	37.8000378	0.6	0.84	30	1.31746	0.2	0.1	365	168236189.3	
L	892278	0.3	56189	2.38567	15.87994091	0.45	0.78	14	1.352646148	0.2	0.1	365	319703086.3	
												Total:	3334603664	kg/year
													9135900.45	kg/day

5.1.2 Our calculations on waste collected according to our formulations which is given as 9135 Tons/Day

2.4. Disposal of Municipal Solid Wastes

Disposal through Dumping

The Corporation disposes waste through landfill or land dumping method. At present there are 4 dumping sites in operation. Waste is brought here from various locations throughout the city as well as from the TSs at Mahalaxmi and Kurla. Refuse and debris are levelled at these sites by means of bulldozers and landfill compactors. The land filling carried out here is open dump tipping. At present there are 3 landfill sites in Mumbai. These are: Deonar, Mulund and Gorai (Figure 2).

Table 4: Amount of Waste Disposed at Dumping Sites

Location	Area (hectares)	Quantity of MSW received (Maximum) (TPD)
Deonar	111.00	6,826
Mulund	25.30	598
Gorai	14.50	2,200
Total	**150.80**	**9,624**

Source: MCGM, Dec. 2004

Two more landfill sites have been proposed: at Kanjurmarg of 82 Ha and at Mulund of 40 Ha (SWM Cell, AIILSG, 2003). Of all the four waste disposal sites, Deonar receives 70 per cent of the total waste generated (Table 4), as this is the largest of all the three dumping sites with an area of 111 ha. All the dumping grounds are nearly 30-40 km north of South Mumbai, which is generating 48 per cent of the total waste of the city. As a result, transportation costs of waste are quite high and approximate to about Rs. 16 lakhs per day[8] Costs for maintenance of dumping ground, waste transportation and hire charges come to Rs. 126 crores per annum and constitute nearly 28 per cent of the total budget allocated for SWM (Davis n.d.). These sites need to be upgraded and the waste appropriately treated as it has been estimated that they will last for only another 5 years (SWM Cell, AIILSG 2004).

5.1.3 Research paper data on number of data collected which is given as 6826 Tons/Day

As we can clearly see the discrepancies in the data,

- The official BMC site stated: 4000 tons/day
- The research paper stated: 6826 tons/day
- Our projections: 9135 tons/day

6)EXPERIMENTATION & RESULTS

6.1) Datasets / Tables

Following are the datasets/tables used:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Ward	Population	Wp	Density(persons per sq km)	Df	Area(km2)	Avg Education level(Education Index)	Ef	Urbanization index(BUA km^2)	Uf	Sf	Sm	Days	Total Waste	
2	A	210926	0.3	16874	1.20622	12.50005926	0.75	0.9	1.85	1.059199719	0.2	0.1	365	34525063.01	
3	B	199550	0.3	70,264	2.80792	2.840003416	0.7	0.88	1.24	1.174647677	0.2	0.1	365	82448779.33	
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5	D	346700	0.3	43,175	1.99525	8.030110017	0.73	0.892	3.37	1.167868186	0.2	0.1	365	102581091.3	
6	E	413662	0.3	56500	2.395	7.321451327	0.65	0.86	3.87	1.211433489	0.2	0.1	365	146928702.4	
7	F/N	698000	0.3	53900	2.317	12.94990724	0.62	0.848	4.62	1.142703725	0.2	0.1	365	223084000.1	
8	F/S	377873	0.3	27000	1.51	13.9952963	0.68	0.872	3.49	1.099747799	0.2	0.1	365	77891464.01	
9	G/N	590,609.00	0.3	65,828	2.67484	8.972002795	0.58	0.832	7	1.312081936	0.2	0.1	365	245493288.7	
10	G/S	377,749.00	0.3	37,775	1.83325	9.999973527	0.6	0.84	5.5	1.220000582	0.2	0.1	365	101023360.8	
11	H/W	495,000	0.3	42,672	1.98016	11.60011249	0.7	0.88	9	1.310341818	0.2	0.1	365	160890435.5	
12	H/E	579123	0.3	31,270	1.6381	18.52008315	0.55	0.82	8	1.172785401	0.2	0.1	365	129867685	
13	M/E	950,000	0.3	29,230	1.5769	32.50085529	0.35	0.74	20	1.246147368	0.2	0.1	365	196646560.4	
14	M/W	580,000	0.3	29,940	1.5982	19.37207749	0.5	0.8	12	1.24777931	0.2	0.1	365	131717766.7	
15	N	660000	0.3	25,423	1.46269	25.96074421	0.55	0.82	15	1.231118182	0.2	0.1	365	138729013.1	
16	K/E	1400000	0.3	92000	3.46	15.2173913	0.6	0.84	14	1.368	0.2	0.1	365	792368111.8	
17	K/W	750000	0.3	29956	1.59868	25.03672052	0.65	0.86	12	1.1917184	0.2	0.1	365	174925197.5	
18	S	800000	0.3	21164	1.33492	37.8000378	0.6	0.84	30	1.31746	0.2	0.1	365	168236189.3	
19	L	892278	0.3	56189	2.38567	15.87994091	0.45	0.78	14	1.352646148	0.2	0.1	365	319703086.3	
20													Total:	3334603664	kg/year
21														9135900.45	kg/day

Fig 6.1.1 Total waste collected from each ward in Mumbai

6.2) Test cases

1. All wards have a consistent "Wp" value of 0.3
2. All wards have consistent "Sf" value of 0.2
3. All wards have consistent "Sin" value of 0.1
4. All wards have consistent "Days" value of 365

These consistent values across all wards suggest they are fixed parameters or test conditions applied uniformly across the dataset.

The data appears to be tracking waste generation and various demographic/geographic factors across different wards (labeled A through S, plus several with compound labels like F/N, F/S, G/N, etc.

6.3) Results

The data shows waste generation information across multiple wards (A through L, plus some compound-named wards like F/N, G/N, etc.), along with various demographic and geographic factors.

Key results from this dataset:

1. Total waste generation: 333,400,364 kg/year (as shown in cell O20)
2. Waste generation per day: 913,600.45 kg/day (as shown in cell O21)

The wards with the highest waste generation are:

- L: 31,970,366.3 kg/year
- G/N: 24,543,288.7 kg/year
- F/N: 22,304,000.1 kg/year

The wards with the lowest waste generation are:

- B: 8,244,877.33 kg/year
- K/E: 7,923,611.8 kg/year
- F/S: 7,780,464.01 kg/year

There appears to be correlation between population and waste generation, though other factors like urbanization index (UI) and education level also seem to influence the results.

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