Food Waste in Asia: Exploring Sources and Consequences Across Bangladesh, Nepal, Sri Lanka, Pakistan, India, China, and Indonesia

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ABSTRACT

In this research, we explore food losses and waste across seven Asian countries: Bangladesh, Nepal, Sri Lanka, Pakistan, India, China, and Indonesia. It shows significant variations in food loss patterns at different stages of the food supply chain. India has the most comprehensive data which shows relatively lower loss percentages, indicating better food management practices. On the other hand, Indonesia has limited data, making it challenging to assess its situation accurately. Countries like Sri Lanka and Nepal face the highest average loss percentages, particularly in their food systems, while China reports the highest losses during the Post-harvest stage and in trading and food services. Fruits and vegetables and staple crops like roots, tubers, and cereals show particularly high loss rates in Sri Lanka, Nepal, and Bangladesh, indicating significant issues in handling and storage management. India, however, manages to keep its losses relatively low, especially for animal products. These can be overcome by adopting some of the strategies that seem to be working for China in managing food wastage. These range from public awareness campaigns to stricter regulation of food wastage, better storage and transport infrastructure, and projects that see surplus food being used. Improved data collection, better infrastructure, and good sustainability practices can help Asian countries reduce food wastage considerably, ensuring food security and achieving a more sustainable food system.

KEYWORDS

Food Loss, Food Waste, Asian Countries, Food Supply Chain, Post-Harvest Losses, Sustainable Practices, Data Analysis, Data Science

1 INTRODUCTION

Food loss and waste (FLW) have emerged as critical global challenges with profound implications for food security, environmental sustainability, and economic stability. As the population across the world is rising continuously, managing food resources efficiently becomes increasingly crucial. In Asia, approximately one-third of food produced for human consumption is lost or wasted, presenting a severe threat to food security and economic stability while exacerbating environmental concerns [3]. The environmental impact of food waste is significant, contributing to greenhouse gas emissions and resource depletion. Economically, it results in substantial financial losses and affects the livelihoods of farmers and stakeholders across the supply chain. The motivation behind this research stems from the urgent need to address these challenges. The Food Waste Index Report 2024 highlights that food waste contributes to 8-10% of global greenhouse gas emissions, emphasizing the necessity for effective strategies to reduce waste [3]. The Asia-Pacific region, which generates over 50% of global food waste in the food service and retail sectors, faces a particularly acute problem [9]. Despite increasing global awareness, many countries lack robust mechanisms to track progress towards the UN's 2030 Sustainable Development Goals (SDGs) related to food waste reduction [10]. This study aims to investigate the extent and impact of food loss and waste across various stages of the food supply chain in selected Asian countries. By analyzing data from countries such as India, Bangladesh, China, Pakistan, Nepal, Sri Lanka, and Indonesia, this research seeks to identify key areas where interventions can be made to mitigate food waste. The primary research questions include: What are the main stages and causes of food loss and waste in these countries? How do food loss and waste patterns vary across different commodity groups? What strategies have been implemented to address these issues, and how effective are they? This research involves a detailed analysis of food loss and waste data, focusing on different stages of the food supply chain, from production and post-harvest to distribution and consumption. The study employs various analytical techniques, including correlation analysis, Principal Component Analysis (PCA), and machine learning models, to understand and predict food waste patterns. This approach allows for the identification of critical factors influencing food waste and the development of targeted interventions. The findings of this research are intended to provide actionable insights for policymakers, businesses, and consumers to enhance food waste management strategies. By examining data and trends, the study contributes to the broader understanding of food loss and waste issues in Asia, offering practical recommendations for reducing waste and improving sustainability.

2 BACKGROUND

Food loss and waste are significant issues impacting global food systems and environmental sustainability. The domain of food loss and waste encompasses various stages of the food supply chain, from agricultural production and post-harvest handling to distribution and consumption. This section provides an overview of the relevant research and methodologies used to address these issues. Previous research has established that food loss occurs primarily during production, post-harvest, and processing stages due to factors such as inadequate infrastructure, poor storage facilities, and inefficiencies in transportation [4]. In contrast, food waste is more prevalent at the retail and consumer levels, driven by overstocking, confusion over date labeling, and consumer behavior [5]. The distinction between food loss and food waste is crucial for designing effective interventions, as food loss requires improvements in supply chain infrastructure, while food waste involves changes in retail practices and consumer habits [8]. The Asia-Pacific region presents a unique context for studying food loss and waste due to its diverse economic conditions and rapid urbanization. Previous studies have highlighted significant food waste issues in countries like India and China, with large quantities of food lost during various stages of the supply chain [7]. For example, in India, an estimated 40% of food produced is wasted, leading to economic losses and food insecurity [7]. Similarly, China's "Clean Your Plate Campaign" and Bangladesh's solid waste management rules represent efforts to mitigate food waste at different levels of the supply chain [2], [6]. Sri Lanka focuses on reducing the post harvest losses through better infrastructure and modern agricultural techniques where as Nepal took Zero Hunger Challenges to eradicate hunger by 2025 [1]. This study builds on existing research by focusing on a comprehensive analysis of food loss and waste data from multiple Asian countries. By employing advanced analytical techniques and examining data trends, the study aims to provide new insights into food waste patterns and the effectiveness of various waste reduction strategies. This approach not only adds to the existing body of knowledge but also offers practical recommendations for improving food waste management in the region.

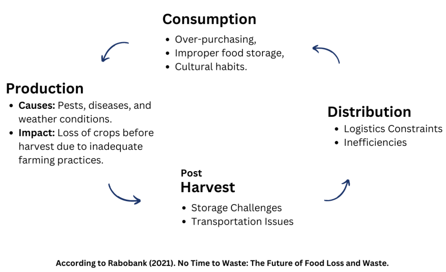

Figure 1: Stages of Food Loss

Figure 1: Stages of Food Loss outlines the main points where food loss occurs in the supply chain. Farm losses happen due to pests, diseases, adverse weather, and inefficiencies in farming practices. Post-harvest losses occur from spoilage during storage and handling, as well as processing inefficiencies. Distribution losses are caused by delays, poor logistics, and mishandling during transportation. Consumer waste arises from over-purchasing, improper storage, and confusion over food labels. Understanding these stages helps in targeting interventions to reduce food waste and improve the efficiency of the food system. In our research of food loss across various stages of the food supply chain, we focused on several key commodity groups: cereals and pulses, fruits and vegetables, roots, tubers and oil crops, animal products, and other items such as stimulants and spices. This selection was guided by a structured methodology aimed at capturing a comprehensive understanding of food waste and its impacts. The choice of these commodity groups was driven by their significance in the food supply chain and their unique characteristics, which influence patterns of food loss. For instance, cereals and pulses, as staple foods, have different storage and handling requirements compared to perishable items like fruits and vegetables. Similarly, the processing and packaging needs of animal and fish products differ considerably from those of staple crops. Our selection process followed a methodical approach, beginning with considerations of shelf life. Each commodity group has varying shelf lives that impact their susceptibility to loss at different stages. Perishable items like fruits and vegetables have shorter shelf lives, making them more prone to spoilage and waste compared to more durable staples such as cereals and pulses. Handling requirements also played a crucial role in our selection. Different commodities necessitate specific handling practices; for example, roots and tubers require particular storage conditions to prevent spoilage, whereas animal products demand stringent temperature controls to ensure safety and minimize waste. Seasonal availability was another important factor. The availability of certain commodities varies with the seasons, affecting their supply and the likelihood of losses. Seasonal variations influence both production and consumption patterns, which are essential for understanding food waste dynamics. Processing and packaging needs were considered as well, as these methods significantly impact food loss. For instance, fish and meat products often require complex processing and packaging solutions, while staple crops might be managed in bulk, each presenting its own set of challenges. Finally, policy and regulatory considerations were taken into account. Different commodity groups may be subject to varying standards and guidelines, which influence how they are managed throughout the supply chain. These regulatory frameworks play a role in shaping food waste patterns. By concentrating on these diverse commodity groups, the research aims to address food loss in a holistic manner, taking into account the specific needs and challenges associated with each type of food product. This approach ensures that the strategies developed are well-suited to the particular requirements of different commodities, ultimately contributing to more effective and sustainable food waste management. The commodity group choice also aligns with Sustainable Development Goal (SDG) 12.3, which aims to halve per capita global food waste at the retail and consumer levels by 2030.

3 METHODOLOGY

Our research on food waste in Asia aims to comprehensively understand the issue of food waste in Asia, focusing on seven key countries: Bangladesh, Nepal, Sri Lanka, Pakistan, India, China, and Indonesia. The research is structured to analyze food waste from multiple perspectives, including the stages of the food supply chain where waste occurs and the patterns of waste across different types of food commodities. This section of the paper will detail the approach which has been taken to achieve these objectives. It will outline the process of data collection, which involves compiling information from various sources, including government reports, industry data, and academic research. The analysis phase involves examining the data to identify trends, patterns, and critical stages in the food supply chain where waste is most prevalent. Additionally, we will explore the differences in food waste patterns among the selected commodity groups, such as cereals and pulses, fruits and vegetables, roots, tubers, oil crops, animal products, and other items.

The methodology also addresses the challenges faced during data collection, such as incomplete data, and varying data quality. We will employ techniques to clean and pre-process the data to ensure its accuracy and reliability for analysis. This includes imputing missing values, encoding categorical variables, and scaling numerical data. In this research, we will employ statistical methods and machine learning algorithms to model the relationships between different variables and predict food waste. We will evaluate the performance of these models using metrics such as Mean Squared Error (MSE) and R-squared (R^2) to ensure the validity of their findings. In summary, the methodology section of this paper on food waste in Asia will provide a detailed account of the research process, including data collection, analysis, modeling, and evaluation, to find out insights to address food waste in the region.

3.1 Project Timeline

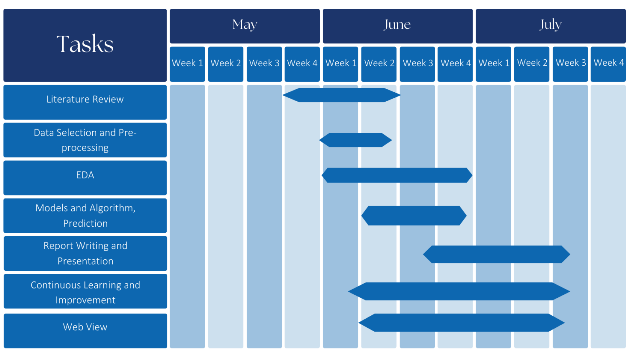

Figure 2: Project Timeline

We created the project timeline carefully to ensure thorough research and analysis. We started in the last week of May with a literature review to understand the global issues related to food waste, setting the stage for our project. In June, we focused on collecting and preparing our data to ensure it was accurate and reliable. We narrowed our focus to specific Asian countries due to data availability issues, which we will detail in our paper in the later sections. Midway through June, we began preparing for our final presentation, organizing our findings into a clear narrative and creating effective data visualization. The first two weeks of July are dedicated to finalizing the report and ensuring clarity and coherence. We also aim to create a web view for the study's findings, making the research accessible and visible. As we neared the end of the timeline, we conducted a thorough review of our report, presentation feedback, and web view to ensure quality. After this thorough process, we submitted our final report, concluding our project.

3.2 Workflow

The workflow diagram (Figure 3) provides a visual representation of the steps involved in data cleaning and pre-processing, which are critical for preparing the dataset for advanced analyses and visualizations. The process begins with raw data collection from various sources. This step took longer than we expected. Though there are online databases on food wastage, they present significant

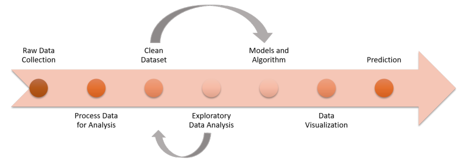

Figure 3: Workflow Diagram

challenges. Not every country has the necessary data for analysis, and data is not available for every year. Additionally, the collection strategies vary for each country, leading to significant data gaps. It was difficult for was to do our research on global food wastage data. After a detailed study, keeping on the project timeline we selected a subset of the collected data from Food and Agricultural Organization (FAO). Then with Initial Data Cleaning, where the first step addresses missing values through imputation. Missing values in selected columns were filled with a specified category to maintain the dataset's integrity, ensuring that subsequent analyses were based on a complete dataset. The next step involves correcting data types by removing non-numeric characters from numerical columns. This ensures that all data is correctly formatted for statistical calculations and modeling, which is essential for accuracy in numerical analysis. Following initial cleaning, Feature Engineering is undertaken, which involves classifying commodities into distinct groups such as cereals, fruits, vegetables, roots, tubers, oil crops, and animal products. A new column was created for this classification, making it easier to identify patterns and trends across different types of food products. The development of an Automated Pipeline includes several tasks designed to streamline the data preparation process. This pipeline manages missing data, encodes categorical variables into numerical formats for machine learning algorithms, and scales numerical data to ensure all variables have a similar range. These steps are crucial for the effective application of machine learning techniques. Correlation Analysis follows, where relationships between numerical variables are explored. This analysis helps in understanding how different factors may influence food waste, providing insights into the interactions between various variables. Next, Principal Component Analysis (PCA) is used for dimensionality reduction. PCA highlights the most significant variables affecting food waste, simplifying the dataset and aiding in data visualization by focusing on the most impactful features. Finally, the Train-Test Split is performed, dividing the dataset into training and testing subsets in an 80:20 ratio. This step is essential for evaluating the performance of machine learning models, ensuring that the models are tested on unseen data and not just fitting the training data. Each step ensures that the data is accurate, consistent, and ready for machine learning applications, ultimately providing the generation of actionable insights to address food waste in selected Asian countries.

3.3 Data collection

The dataset spans from 2000 to 2022 and includes 25,416 entries from 123 countries. Sourced from the FAO Food Loss and Waste Database, it provides comprehensive insights into food loss and waste across numerous nations, offering crucial information for tackling and understanding the global challenge of food waste. Initially, we aimed to address food waste on a global scale. However, due to limitations in data availability, we redirected our focus specifically to Asia. The dataset we utilized for this study is comprehensive and structured to provide detailed insights into food loss and waste across the region. It includes data collected from 2000 to 2022, covering 123 countries, with a total of 25,416 entries. We selected a subset of the dataset consisting of 2,435 entries, focusing on seven Asian countries: Bangladesh, Nepal, Sri Lanka, Pakistan, India, China, and Indonesia. This subset includes several columns related to loss percentages, causes, and data collection methods. Each column contains specific types of data, including numeric values, categorical entries, and other relevant details. This dataset offers a detailed look into different commodities and stages of the food supply chain, facilitating a detailed understanding of food loss and waste issues within these selected countries. Data Source: Food and Agricultural Organization of the United States(FAO)

3.4 Data Cleaning and Pre-Processing

Data cleaning and pre-processing are crucial for ensuring that the dataset is well-prepared for analysis and visualization. Initially, we addressed missing values by imputing them with a specified category in selected columns, which helped to maintain the integrity of the dataset and ensure that subsequent analyses were meaningful. Additionally, we corrected data types by removing non-numeric characters from numerical columns, ensuring that all data was properly formatted for statistical calculations and modeling. Feature engineering played a key role in simplifying our analysis. We created a new column to classify individual commodities into distinct groups, such as cereals, fruits, vegetables, roots, tubers, oil crops, and animal products. This classification made it easier to identify patterns and trends across different types of food products.

In the data pre-processing phase, we developed an automated pipeline to handle various tasks, including managing missing data, encoding categorical variables, and scaling numerical data. This pipeline ensured that the dataset was consistent and suitable for machine learning algorithms. We also conducted a correlation analysis to explore relationships between numerical variables, which helped us understand how different factors might influence food waste. Principal Component Analysis (PCA) was used to reduce the dimensionality of the dataset, facilitating data visualization and highlighting the most significant variables affecting food waste. To evaluate our machine learning models, we performed a train-test split, dividing the dataset into training and testing subsets in an 80:20 ratio. These comprehensive data processing and cleaning steps were essential for preparing the dataset for advanced analyses and visualizations. By ensuring the accuracy and consistency of the data, we could effectively apply machine learning techniques and create insightful visualizations to communicate our findings on food waste across the selected Asian countries.

3.5 Data Visualization

The treemap in Figure 4 illustrates the distribution of data across the seven countries studied. India has the largest share of the dataset at 54.7%, followed by Bangladesh at 23.0%. China, Pakistan, Nepal, Sri Lanka, and Indonesia have smaller shares, with Indonesia having

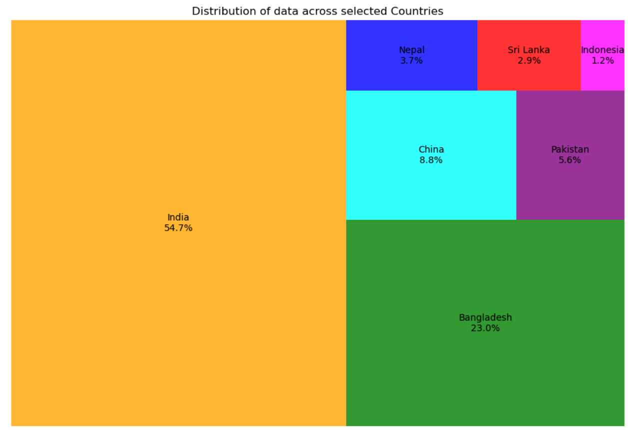

Figure 4: Distribution of data across Selected countries

the smallest at 1.2%. This distribution highlights that the majority of the data comes from India and Bangladesh, which may significantly influence the overall findings and insights of the study. This

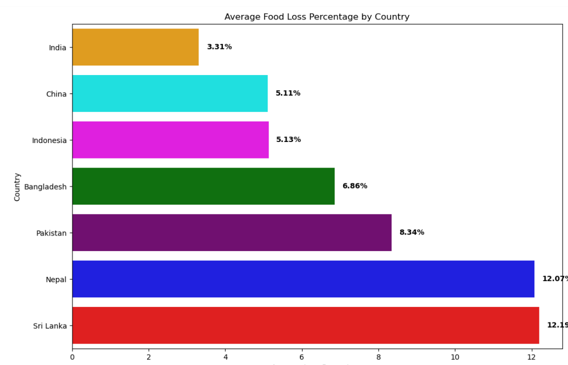

Figure 5: Average food loss percentage in the selected countries

figure displays the average food loss percentage across the selected countries, revealing notable variations in food loss levels. India has the lowest average food loss percentage at 3.31%, indicating relatively efficient food management practices compared to other countries. In contrast, Sri Lanka and Nepal exhibit the highest average loss percentages, with 12.19% and 12.07%, respectively. This suggests significant inefficiencies in food handling and storage in these countries. China, with an average loss of 5.11%, and Indonesia, at 5.13%, experience moderate levels of food loss, which are higher than in India but lower than in Sri Lanka and Nepal. Bangladesh follows with an average loss of 6.86%, reflecting a substantial but not extreme level of food waste. Pakistan shows an average loss of 8.34%, indicating a higher level of food waste compared to the countries with lower percentages. These variations highlight the need for targeted interventions to address food loss in specific regions, with a particular focus on improving practices in Sri Lanka and Nepal where the losses are most pronounced. Figure 6 provides a detailed view of food loss at various stages of the food supply

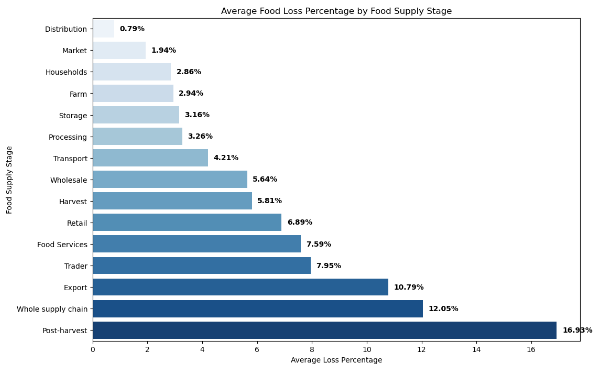

Figure 6: Food loss in different stages of Food supply

chain, highlighting where the most significant losses occur. The data reveals a broad spectrum of loss percentages across different stages, reflecting varying degrees of inefficiency and challenges in food management. The figure shows that food loss is highest at the Post-Harvest stage, with an average loss percentage of 16.93%. This indicates substantial losses occurring immediately after harvest, which could be due to factors such as inadequate storage conditions, handling practices, or processing inefficiencies. This high percentage underscores the critical need for improvements in post-harvest technologies and practices. The Whole Supply Chain stage follows with an average loss of 12.05%, suggesting that inefficiencies extend beyond post-harvest handling and affect the entire supply chain. This stage encompasses multiple processes from production through to consumption, indicating that systemic improvements are needed to address losses at various points in the chain. Export stages also show significant losses, with an average of 10.79%. This reflects challenges in maintaining food quality and minimizing waste during transportation to international markets. Similarly, the Trader and Food Services stages exhibit high losses at 7.95% and 7.59%, respectively, pointing to issues in food handling and preparation at these stages. Retail and Harvest stages show average losses of 6.89% and 5.81%, respectively, highlighting that food waste occurs not only during storage and handling but also from the initial stages of production. The Wholesale stage, with an average loss of 5.64%, further emphasizes the importance of efficient distribution and storage practices. Transportation and Processing stages experience average losses of 4.21% and 3.26%, respectively. Although these percentages are lower than the post-harvest and whole supply chain stages, they still represent significant areas where improvements can be made to reduce food waste. Farm and Storage stages, with average losses of 2.94% and 3.16%, respectively, show that food loss begins early in the supply chain but remains relatively lower compared to later stages. Households, at 2.86%, reflect losses occurring at the consumer level, which often stem from spoilage, over-purchasing, or improper storage. The Market stage, with the lowest average loss of 1.94%, and the Distribution stage, at 0.79%, represent the final stages of the supply chain before food reaches the consumer, where losses are relatively minimal. Overall, the figure illustrates that food losses are significant at multiple stages, with post-harvest and whole supply chain stages being particularly critical areas for intervention. Addressing inefficiencies and implementing targeted strategies at these stages can lead to substantial reductions in overall food waste.

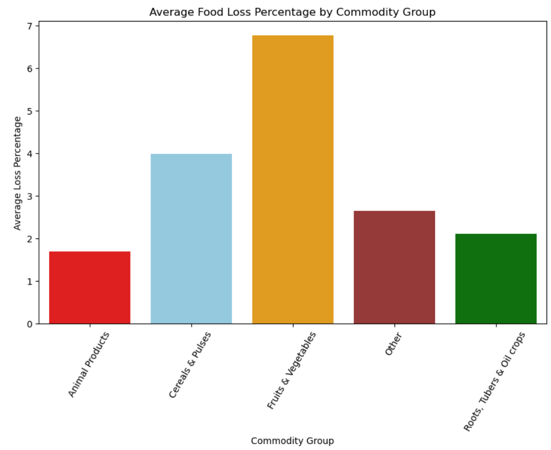

Figure 7: Average food loss in different commodity groups

Figure 7 provides a detailed analysis of average food loss percentages across different commodity groups, revealing significant variations in waste levels. Fruits and vegetables show the highest average loss percentage at 6.78%. This substantial level of waste suggests inefficiencies in handling, storage, and processing, particularly in countries such as Sri Lanka and Nepal. The high loss rates indicate challenges like inadequate refrigeration, poor handling practices, and insufficient preservation methods. Enhancing storage facilities and supply chain management for fruits and vegetables could lead to considerable reductions in food waste. In comparison, cereals and pulses exhibit a lower average loss percentage of 3.99%. Although this is less severe than for fruits and vegetables, it still points to notable waste, likely due to issues in bulk storage or losses during transportation and handling. Improving storage solutions and management practices could help mitigate these losses. Animal products show the lowest average loss percentage at 1.69%. This relatively low figure may be attributed to effective preservation techniques and more efficient supply chains. However, maintaining and further improving these practices is essential to prevent potential increases in loss rates. The category labeled "Other," which encompasses a variety of less standardized items, has an average loss percentage of 2.64%. This moderate level of waste suggests that while improvements in handling and storage are necessary, they may not be as urgent as those needed for commodity groups with higher loss percentages. Roots, tubers, and oil crops have an average loss percentage of 2.11%. Although this figure is lower compared to fruits and vegetables, it still indicates a need for better preservation techniques, particularly for these staple food items that are crucial for food security. Overall, the insights from Figure 7 emphasize the importance of targeted interventions to address food loss, especially in the fruits and vegetables category, where losses are most pronounced. By focusing on improving storage, handling, and processing practices, it is possible to make significant strides in reducing overall food waste and enhancing food security.

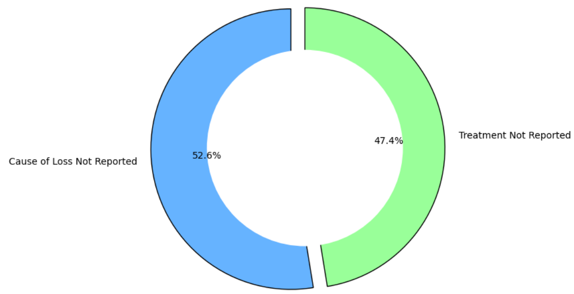

Figure 8: Not reported case (Cause of Loss and Treatment)

The data reveals significant gaps in reporting critical information related to food losses and waste. Specifically, 52.6% of the entries are missing details on the 'cause_of_loss', while 47.4% lack information on the 'treatment'. These missing data points highlight a substantial portion of unreported information that is essential for understanding and addressing food loss issues comprehensively. The lack of information on 'cause_of_loss' means that over half of the data entries do not specify why the food was lost, which impedes targeted intervention strategies. Similarly, the absence of 'treatment' data for nearly half of the entries limits the ability to assess how lost food was managed or handled post-loss. Addressing these reporting gaps is crucial for improving data accuracy and developing effective solutions to reduce food waste.

3.6 Machine Learning Techniques

We employed several Machine-Learning techniques to analyze the dataset and derive meaningful insights. Linear Regression was used to model the relationship between a dependent variable and one or more independent variables using a linear equation. This technique assumes that the dependent variable can be predicted as a linear combination of the independent variables, providing a straightforward method to quantify and understand these relationships. Decision Trees were employed as a non-linear modeling technique. Decision Trees split the data into subsets based on the values of input features, creating a tree-like structure of decisions and their possible consequences. This approach helps in visualizing and understanding the decision-making process behind the predictions. To enhance the accuracy and robustness of our models, we utilized Random Forests, an ensemble learning method that aggregates multiple decision trees. By combining the predictions from several trees, Random Forests improve overall model performance and reduce the likelihood of over-fitting. We assessed model performance using Mean Squared Error (MSE), which measures the average squared difference between actual and predicted values. Lower MSE values indicate better model performance, reflecting more accurate predictions. Additionally, we evaluated the models using R-squared (R^2), which indicates how well the independent variables explain the variance in the dependent variable. R^2 values range from 0 to 1, with higher values suggesting that the model explains a greater proportion of the variance, thereby demonstrating better performance. These machine learning techniques were crucial for analyzing the complex dataset and deriving insights into food waste patterns

Model	Mean Squared Error (MSE)	R-squared (R^2)
Linear Regression	3.7057436529808743	0.9376189193866802
Decision Tree	12.843922484909456	0.7837902890887032
Random Forest	2.8519039018324457	0.9519921333310398

Figure 9: Performance Metrics of Machine Learning Models for Predicting Food Waste

across the different stages of the food supply chain and among various commodity groups in the selected Asian countries. The table presents the performance metrics of three machine learning models—Linear Regression, Decision Tree, and Random Forest—used to predict food waste patterns in the study "Food Waste in Asia: Exploring Sources and Consequences Across Bangladesh, Nepal, Sri Lanka, Pakistan, India, China, and Indonesia." The performance of these models is evaluated using Mean Squared Error (MSE) and R-squared (R^2) as metrics.

Linear Regression has a relatively low MSE of 3.7057, indicating that the model's predictions are close to the actual values. The R-squared value of 0.9376 suggests that approximately 93.76% of the variance in the dependent variable (food waste) is explained by the independent variables in the model. This high R^2 value reflects a strong linear relationship between the variables.

The Decision Tree model shows a higher MSE of 12.8439, indicating larger prediction errors compared to the Linear Regression model. The R-squared value of 0.7838 suggests that about 78.38% of the variance in food waste is explained by the model. While this is lower than the R^2 value for Linear Regression, it still demonstrates a substantial ability to capture the relationship between variables. However, the higher MSE indicates that the Decision Tree model may be less accurate in its predictions. The Random Forest model outperforms both Linear Regression and Decision Tree models, with the lowest MSE of 2.8519, indicating the most accurate predictions among the three models. The R-squared value of 0.9520 is the highest, showing that 95.20% of the variance in food waste is explained by the model. This high R^2 value and low MSE highlight the model's robustness and superior predictive power. The results demonstrate that the Random Forest model provides the best performance, with the lowest prediction error and highest explanatory power. Its ability to handle complex datasets with multiple features and reduce overfitting makes it the most suitable model for predicting food waste patterns in this study. Linear Regression also performs well, offering a good balance of simplicity and accuracy. However, the Decision Tree model, despite its ability to capture non-linear relationships, has higher prediction errors, indicating it may not be as effective as the other two models in this context. These findings suggest that Random Forest is the most reliable model for informing strategies to reduce food waste, given its superior accuracy and robustness. Linear Regression, with its high R^2, can also be useful for understanding the linear relationships between factors influencing food waste.

3.7 Result

The analysis of food losses and waste across selected Asian countries reveals significant variations in data availability and loss percentages at different stages of the food supply chain. India stands out with the most comprehensive data on food losses and waste, providing detailed insights into various aspects of the food supply chain. In contrast, Indonesia has the least available data, which limits the scope of analysis for this country. Sri Lanka and Nepal exhibit the highest average loss percentages, suggesting severe inefficiencies in their food systems. Conversely, India shows the lowest average loss percentages, reflecting relatively better management practices. It is important to note that there are gaps in the data, with 2,155 entries lacking information on ‘cause_of_loss‘ and 1,945 entries missing data on ‘treatment‘. China reports the highest average loss percentage at the Post-harvest stage, with losses reaching 47.5%. Additionally, China experiences significant losses in the Trader and Food Services stages, with average losses of 19.93% and 16.78%, respectively. Nepal shows considerable losses throughout the entire supply chain, with an average loss of 37%, and faces substantial losses specifically in the Retail stage, averaging 19.42%. In Bangladesh, notable losses occur during the Harvest stage (12.4%) and at the Households stage (3.54%). Pakistan also demonstrates significant losses in the Retail stage, with an average of 19.88%. India consistently reports lower losses across various stages, with the Market stage showing the lowest loss percentage at 1.94%. Sri Lanka experiences moderate losses at the Farms stage, with an average of 7.05%. Fruits and vegetables emerge as a critical area for improvement due to their high average loss percentages. Sri Lanka and Nepal report the highest losses in this category, with averages of 12.18% and 14.05%, respectively, indicating potential inefficiencies in handling and storage practices. Bangladesh faces the highest losses in the Roots, Tubers, and Oil Crops category, with losses reaching 20%, highlighting significant challenges in preserving and storing these staple food items. In the Cereals and Pulses category, both Sri Lanka and Bangladesh report higher losses, suggesting potential issues related to harvesting, storage, or transportation. In contrast, India shows the lowest average loss percentage for Animal Products at 1.46%, which may reflect effective preservation techniques or a smaller market share of these products. Overall, the findings underscore critical areas for intervention in food loss management across Asia. Addressing these inefficiencies will require targeted strategies tailored to the specific conditions and needs of each country, with a focus on improving practices related to handling, storage, and distribution to reduce overall food losses. Countries can adopt several of China’s effective food waste management strategies. Launching public awareness campaigns similar to China’s "Clean Your Plate" initiative can encourage mindful eating habits, such as ordering appropriate portions and taking leftovers home. Implementing strict regulations to limit food waste in food service establishments is also crucial. This includes setting guidelines for portion sizes, limiting buffets, and promoting take-home leftovers to reduce waste. Investment in enhancing food storage and transportation systems is essential to reduce post-harvest losses. Building modern storage facilities and improving logistics ensures that food reaches consumers in good condition. Establishing food banks and partnering with charities to redistribute surplus food can help minimize waste and address food insecurity. Encouraging donations from restaurants, supermarkets, and food producers can further support this effort. Developing comprehensive policies that address all stages of the food supply chain is critical. These policies should include incentives for businesses to adopt sustainable practices and support research in food waste reduction. Additionally, educating farmers, retailers, and consumers about best practices in food handling, storage, and preparation can significantly reduce waste. Training programs can teach efficient techniques and promote proper food usage and storage. By adopting these multifaceted approaches inspired by China’s successful strategies, countries can effectively reduce food waste, improve food security, and promote sustainability.

3.8 Limitations and Future Scope

One major limitation is the lack of comprehensive and consistent data on food waste, making it challenging to analyze and develop effective policies. Technological and infrastructure constraints, such as inadequate storage facilities and high costs of advanced technologies, further exacerbate the problem. Cultural and behavioral factors, including over-purchasing and traditional agricultural practices, contribute significantly to food waste. Additionally, fragmented efforts and a lack of coordinated policies at national and regional levels hinder effective food waste management. Improving data collection and analysis is critical for accurately tracking and managing food waste. Developing robust data collection systems and adopting standardized methodologies can help create a clearer picture of food waste patterns. Infrastructure development, such as building modern storage facilities and enhancing transportation systems, can significantly reduce post-harvest losses and ensure that food reaches consumers in good condition. Public awareness and education campaigns are essential to change consumer behaviors and reduce waste. These campaigns can promote sustainable consumption practices, such as proper food storage, portion control, and reducing over-purchasing. Additionally, implementing comprehensive and coordinated policies at national and regional levels can support effective food waste management. Policies should incentivize businesses and consumers to adopt sustainable practices and facilitate food redistribution initiatives to ensure surplus food reaches those in need. By focusing on improving data collection, enhancing infrastructure, promoting public awareness, and implementing supportive policies, significant progress can be made in reducing food waste, improving food security, and promoting sustainability in Asia.

4 CONCLUSION

Addressing food waste in Asia requires a comprehensive approach that includes improving infrastructure, adopting innovative technologies, and promoting public awareness. Each country has unique challenges and opportunities, but common themes include the need for better storage and transportation systems, education on sustainable practices, and effective redistribution of surplus food. A significant issue that must be tackled is the substantial amount of missing data on food waste. Specifically, over half of the data entries lack information on the causes of food loss, and nearly half are missing details on how the lost food was treated. These gaps in reporting hinder our ability to fully understand the underlying reasons behind food waste and to devise targeted solutions. By addressing these reporting deficiencies and improving data collection, we can better identify the root causes of food waste and develop more effective strategies. This will enable Asian countries to make substantial progress in reducing food waste, enhancing food security, and promoting sustainability. Learning from successful initiatives and closing these data gaps will lead to more precise interventions and a more effective approach to managing food waste.

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5 TASK DISTRIBUTION

Table 1: List of Task Distribution

Name	Task
Sarah Islam Momo	• Project Preparation • Reviewing research papers on food waste • Writing Expose PDF • Creating and editing PowerPoint presentation • Slide design • Data Collection • Data cleaning and pre-processing • Creating new features • Feedback Integration • Develop Methodology for the research • Data Analysis and data cleaning • EDA • Developed an interactive dashboard and utilized Streamlit to create the web view for efficient data visualization and user interaction. • Writing Final Report (Abstract, Methodology, Result, Conclusion)
Md Asif Siddique	• Data Analysis • Data Cleaning and pre-processing • EDA • Reviewing research papers • Creating PowerPoint slides • Work on the Machine learning model • Web view creation • Writing Final Report (Result)
Nazia Nusrat Ima	• Reviewing multiple research papers to develop an understanding of the topic • Creating and editing PowerPoint slides • Literature Review and Background Studies • Writing paper (Introduction, Background)