Enhancing agricultural feedback analysis through Voice User Interface and Deep Learning Integration

by

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Abstract

A substantial amount of critical information in various sectors hinges on consumer feedback, which influences everything from product adoption to overall satisfaction. The agricultural sector, in particular, depends heavily on farmers, whose feedback dictates the success of products and highlights associated challenges. This study aligns with this perspective, emphasizing the importance of understanding farmers' needs to assist tractor manufacturing industries. However, communication with farmers poses significant challenges, especially when dealing with a large number of farmers across multiple locations. Even in single locations with fewer farmers, information often passes through intermediaries, leading to potential deviations from the original message and creating communication gaps. To address these challenges, we partnered with Dexer, a VUI (Voice User Interface) application-based company. Dexer's features, including voice recognition accuracy, offline capability, and media support, aids in streamlining the feedback process. This collaboration allows farmers to simply speak into the app to record their feedback, ensuring the information remains raw and unaltered. The partnership aims to enhance communication efficiency and bridge potential gaps in the feedback collection process. In addition to our primary objective, we undertook an exploratory task to analyze various aspects of our dataset. Initially, we used BERT for sentiment analysis on farmer feedback. Later, we compared BERT with RoBERTa, which is specifically designed for sentiment analysis tasks. The primary result we sought from our model was understanding the concrete reasons behind farmers' ratings. To address this, sentiment analysis was employed to provide reliable information that the responsible parties can use to take informed actions. This study not only bridges the communication gap between farmers and manufacturers but also provides a robust framework for utilizing modern AI techniques to improve product development and adoption in the agricultural sector.

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Acknowledgments

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Dedication

My gratitude towards my family is always beyond words. Their unwavering support, love and encouragement throughout my personal as well as academic journey is priceless. I dedicate this work to them for being the strong pillars of my life and for keeping me motivated during the tough times.

Chapter 1

Introduction

The swift advancement and widespread adoption of digital technologies have been celebrated as the 'fourth industrial revolution.' This era is marked by a merging of technologies that increasingly blur the boundaries between the physical, digital, and biological realms (Schwab, 2016)[1]. A report by the World Bank, the African Development Bank, and the African Union highlights that the strategic application of information and communication technology (ICT) to the agricultural industry—which is the largest economic sector in most African countries—presents a significant opportunity for economic growth and poverty alleviation across the continent (Baumüller H, 2018)[2].

In line with these transformative changes, the agriculture sector is undergoing a significant shift, where the gathering and utilization of data for decision-making are gaining heightened significance. The role of information and communication technology (ICT) in agriculture has significantly improved information sharing among farmers and other stakeholders. This enhanced information exchange is used as a means to achieve economic growth and increase welfare, as it enables better decision-making and more efficient production processes (Liu et al., 2021)[3].

Two primary challenges exist in analyzing the impact of ICTs on agricultural development. First, ICTs influence a broad spectrum of outcomes beyond agriculture; their capacity to enhance economic opportunities across various sectors leads to significant macroeconomic effects (Röller and Waverman, 2001[4]; Torero et al., 2006[5]; Gruber and Koutroumpis, 2011[6]). Second, ICTs encompass a diverse range of technologies, including computers, the Internet, radio, television, and mobile phones, among others. Consequently, the impact of ICTs varies significantly depending on the specific technology employed. In the agricultural sector, ICTs hold significant potential to enhance farmers' access to both public and private information. It can connect buyers and sellers, facilitate the collection of agricultural data, and improve access to financial services.

In parallel with the advancements in ICT, the tractor implements market has experienced notable growth in recent years, driven by the increasing demand for mechanization within the agricultural sector. Mechanized farming offers numerous benefits, including enhanced efficiency, reduced labor costs, increased productivity, and improved quality of output. These advantages have propelled the adoption of tractor implements among farmers globally, thereby driving market expansion. Moreover, the burgeoning global population and the consequent rise in food demand have necessitated the adoption of advanced farming techniques and equipment, further stimulating the demand for tractor implements. Government initiatives promoting agricultural mechanization, alongside the availability of subsidies for farmers, have also significantly contributed to market growth. According to the recent Tractor Implements Market Size, Share & Trends Analysis Report (2022)[7], analysis indicates that the tractor implements market is projected to witness a compound annual growth rate (CAGR) of 5% from 2022 to 2030. Key factors such as increasing investment in agriculture, technological advancements in tractor implements, and the imperative for efficient farming practices are expected to drive market growth. Additionally, the emergence of precision agriculture, which leverages advanced technologies to optimize agricultural processes, is anticipated to create lucrative opportunities for the tractor implements market. Recent trends in the tractor implements market include the integration of GPS and telematics technology in implements for precise field mapping, remote monitoring, and data recording. Manufacturers are also focusing on developing lightweight and durable implements that offer reduced fuel consumption and enhanced efficiency. Furthermore, the advent of electric tractors and implements is gaining traction, driven by the need for environmentally friendly and sustainable farming practices.

Several factors contribute to the growth of ICTS in agriculture, including the increasing adoption of mechanized farming practices, a rising global population that drives higher food demand, and government initiatives promoting agricultural mechanization. Technological advancements in tractor implements, such as GPS integration and precision farming techniques, further propel market expansion. Additionally, the growing importance on contract farming and a heightened focus on sustainability practices are expected to enhance the demand for tractor implements. Overall, the outlook for the tractor implements market appears highly positive, with abundant opportunities for growth and innovation. The feedback from farmers on the prototypes of tractors and implements has been instrumental in enabling various companies to enhance their market competitiveness. This valuable feedback has not only mitigated economic losses but also increased profitability. However, traditional data collection methods, which relied heavily on pen and paper, proved inefficient and outdated. Consequently, there was a pressing need to adopt more efficient data collection techniques. One promising method was the use of a Voice User Interface (VUI) application. To explore this innovation, we partnered with a company named Dexer.

Figure 1.1: *Dexer (Source : https://www.dexerspeed.com)*

Given the contradictory findings in existing literature regarding optimal data collection methods, we designed two distinct scenarios to evaluate their effectiveness. The first scenario, Dexer Edge, utilized an online form that could be edited via text input or voice commands. The second scenario, Dexer Natural, employed an AI-based approach, allowing users to input data conversationally, with the AI subsequently processing and organizing the data into a structured, tabular format. This study aims to determine which method offers superior efficiency and accuracy in data collection within the agricultural sector and further determines the transformer model that is the most efficient to process this data. This paves way to the following problem statements discussed in the next section.

1.1 Problem Statements

1. To perform a comparative analysis on two different data collection scenarios, Dexer Edge and Dexer Natural, to evaluate which approach provides the most accuracy and efficiency.

2. To determine the most suitable method to analyse and review farmers' feedback accurately.

3. To perform a comparative analysis on two transformer models - BERT and RoBERTa - to determine which model translates higher efficacy in processing the sentiments.

1.2 Thesis outline

The thesis is divided into 5 chapters. Chapter 1 discusses the introduction to the study while the Chapter 2 dives into the related literature review pertaining and relevant to the field. Chapter 3 talks comprehensively about the tools and techniques used for data processing, specifically two data collection scenarios, the engines used for it and finally a comparative study on both the scenarios to determine which one outperforms the other. Chapter 4 discusses about Sentiment Analysis and various Transformer models used for this purpose. It consists of the methodology used for this particular study and discusses the results and analysis obtained from the study conducted. Lastly, Chapter 5 concludes the work.

Chapter 2

Related Work

Innovations in information and communication technologies (ICTs) are essential to the digital revolution that the agriculture industry is experiencing. Combining Voice User Interfaces (VUIs) with Deep Learning (DL) to improve agricultural feedback processing is one area of great promise. In this review, the limitations of previous work are discussed and contemporary research at this confluence is examined with an emphasis on transformer models such as Roberta.

2.1 Deep learning for analysing agricultural reviews

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in particular, are two deep learning algorithms that have shown a great deal of promise for agricultural data analysis. CNNs are good at identifying images, which makes them appropriate for using images to assess the health of plants (Khalid and Karan 2023)[8]. However, RNNs are very good at processing sequential data, which makes them perfect for examining time-series sensor data that is gathered from farms (Ndikumana et al., 2018)[9].

2.2 VUIs in Agriculture

Farmers now have a hands-free and maybe easier way to give tractor implement feedback—thanks to VUIs. Research such as (Osman et. al 2022)[10] show that VUIs hold great potential for use in agricultural settings. They discovered that voice assistants were quickly embraced by farmers for activities such as information retrieval and weather monitoring.

2.3 Integration of VUI and Deep Learning

Agricultural feedback analysis has fascinating new possibilities when VUIs and DL are integrated. Through a VUI, farmers can directly voice their opinions about crop health, insect problems, or field conditions. Then, using deep learning models, this audio data may be analyzed to extract pertinent information and spot trends. Reports and alarms can be generated, and farmers can receive advice in real time based on this data. Besides these applications, with the integration of VUIs and deep learning models, agricultural feedback systems can also function more effectively. With the help of this connection, data may be gathered in real time via voice commands and analyzed right away utilizing deep learning algorithms.

2.4 Sentiment Analysis

Neural network architectures known as transformer models have completely changed the field of natural language processing (NLP). With the ability to examine intricate links between sentences, these models can greatly enhance text classification and speech recognition. Sentiment analysis of agricultural text data has demonstrated the effectiveness of deep learning techniques, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Bharman et al., 2022)[11]. From farmer reviews, these programs can efficiently extract emotion and pinpoint important subjects.

2.5 Deep learning models for feedback analysis

Recent advances in deep learning architecture, particularly transformer models such as BERT and RoBERTa, has produced state-of-the-art results in a variety of natural language processing (NLP) problems. BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa (A Robustly Optimized BERT Pretraining Approach) are pre-trained on vast amounts of text data, enabling them to capture nuanced meanings in feedback, which is crucial for deriving actionable insights (Devlin et al., 2018)[12]. RoBERTa, a pre-trained transformer, is one of the models that excels in comprehending intricate contextual relationships in text (Liu et al., 2019)[13]. From spoken language, RoBERTa can extract important details about crop health, insect issues, and other agricultural concerns (Sun et al., 2019)[14] Because of this, they are perfect for examining detailed farmer feedback and may even bring attention to particular areas of tractor implement performance.

Chapter 3

Comparative Analysis on Data Collection Scenarios

3.1 Introduction

In this chapter, a detailed account of the data collection process is provided that was undertaken for this research. The methodology is divided into two distinct scenarios, each tailored to capture the necessary data comprehensively and accurately. This approach ensures that the collected data is robust, relevant, and suitable for the analysis required to meet the research objectives. We will begin by understanding the two different data collection scenarios utilized in this study. As introduced in the initial sections, the Dexer Edge scenario is characterized by a form-based data collection method, while the Dexer Natural scenario leverages advanced AI-based techniques. Each of these scenarios is described in detail below to elucidate the specific methodologies employed and the rationale behind their selection.

3.1.1 Dexer Edge

To comprehend the functionality of Dexer Edge, it is essential to delve into the workings of the form-based data collection method. Data-collection method using form-based applications would be inexpensive, easy to use, and applicable to widely varying types of studies. It allows end-users who have received minimal training, do not have a significant level of technical proficiency, or education to use the method to enter data efficiently and in a consistent way that minimizes input errors and loss of data.

Key Characteristics of Form-Based Data Collection

Before detailing our specific course of action, it is important to highlight some key characteristics of the form-based data collection method employed in the Dexer Edge scenario. These characteristics underscore the strengths and capabilities of the method, ensuring it meets the demands of various research settings:

- Effortless Data Transformation:
  - The form-based method excels in converting raw speech entries into well-organized, structured data. This transformation process is designed to be seamless, ensuring that the collected data is readily usable for analysis and reporting.
  - Advanced speech recognition technology accurately captures spoken inputs and transcribes them into text. This transcription is then formatted into predefined data fields, ensuring consistency and organization.
- Industry-Tailored Expertise:
  - The data collection forms are specifically trained to understand and interpret industry and company-specific terminology and vocabulary. This ensures that the data collected is relevant and accurate, reflecting the unique context of the study.
  - Customized dictionaries and language models are integrated into the system, allowing it to recognize and correctly interpret specialized terms. Regular updates and training enhance the system's ability to stay current with industry trends and terminology.
- Real-Time Error Handling:

- One of the standout features of this method is its real-time error handling capability. The system allows for immediate voice playback, enabling users to swiftly correct any errors, thus ensuring near-perfect data accuracy.
- During data entry, users can playback their speech inputs to verify accuracy. If discrepancies are identified, corrections can be made on the spot, significantly reducing the error rate and enhancing data reliability.

- Seamless Cloud Integration:
  - The form-based system securely uploads voice-captured data to the cloud with zero lag time. This ensures that data is safely stored and easily accessible from anywhere, facilitating collaboration and data management.
  - Leveraging robust cloud infrastructure, the system automatically synchronizes data entries with the cloud in real-time. This integration ensures data security through encryption and provides scalability to accommodate large volumes of data.

- Enhanced Data Accessibility:
  - The method enhances data accessibility by providing instant access to searchable voice-captured data. This capability significantly streamlines workflow efficiency, enabling users to quickly retrieve and utilize the data as needed.
  - Data entries are indexed and stored in a searchable format, allowing users to perform quick searches using keywords or phrases. This feature improves the speed and ease with which data can be accessed and analyzed, supporting efficient decision-making processes.

Fabrication and Testing of Parameters

With the characteristics of the form-based data collection method in mind, our next step was to fabricate parameters that could capture diverse data types, including numbers, alphabets, alphanumeric sequences, symbols, and paragraphs. These parameters were meticulously designed to ensure comprehensive coverage of all relevant variables, thereby enriching the dataset with varied and nuanced information.

Once the parameters were conceptualized, they underwent rigorous testing to validate their functionality and usability. This testing phase involved simulating real-world scenarios and inputting different data types into the parameters to assess their accuracy and reliability. Any discrepancies or inconsistencies were identified and addressed through iterative refinement, ensuring that the parameters met the desired standards of data capture. Figure 3.1 shows a snapshot of Dexer Edge which was used for getting feedback from farmers on various implements. The customer feedback form was also designed as shown in the figure to get the daily feedback from farmers so that this app can be tested for its usage.

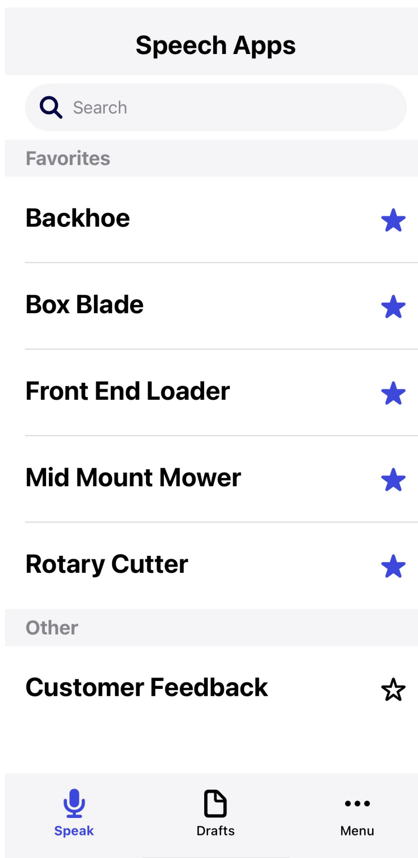

Figure 3.1: *Snapshot of Dexer Edge containing various feedback forms*

3.1.2 Addressing Connectivity Challenges

Recognizing the limited internet access in farming areas, we aimed to bridge this connectivity gap to ensure seamless data collection. Leveraging Dexer's capabilities, we devised a solution that enabled farmers to use the data collection app even in areas with no internet connectivity.

Farmers could simply record their inputs within the app, utilizing the predefined parameters, while working in the field. These inputs were saved as drafts within the app until the farmer returned to an area with internet connectivity. Upon reconnecting to the internet, the drafts could be effortlessly uploaded to the cloud, ensuring that no data was lost and allowing for real-time synchronization of collected information. Figure 3.2 depicts the usage of a farmer trying to input an audio feedback by leveraging the microphone option integrated in the app.

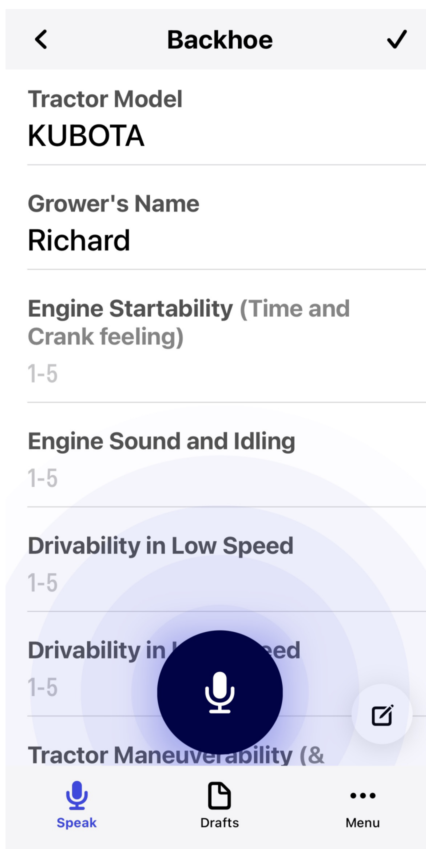

Figure 3.2: *Snapshot of farmer inputting an audio feedback*

Integration of Media Capabilities

Understanding the importance of visual data in accurately documenting agricultural challenges and activities, we devoted considerable time to integrating media capabilities into the data collection application. This enhancement allowed farmers to not only input text-based information but also add images and videos directly from their mobile devices.

The addition of media capabilities was a significant milestone in the development process, as it provided farmers with a powerful tool for capturing and sharing visual evidence of issues encountered in the field. This feature facilitated better communication and understanding between farmers and agricultural experts, enabling more informed decision-making and problem-solving. Figure 3.3 shows the preview of the dashboard depicting the collected farmer feedback.

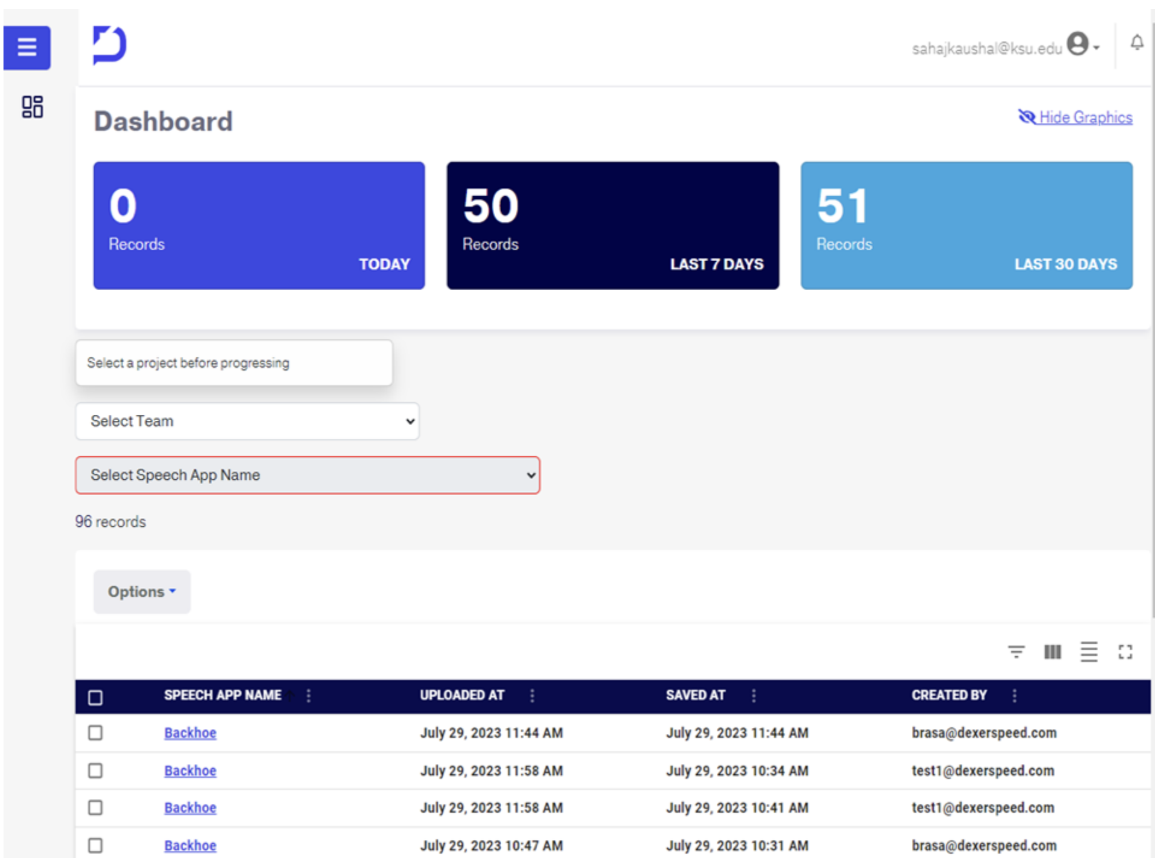

Figure 3.3: *Dashboard of collected farmer feedback*

3.1.3 Dexer Natural

Dexer Natural employs advanced AI capabilities to analyze the data provided by farmers, offering a comprehensive solution for data processing and interpretation. Below are the key functionalities of Dexer Natural that enhance its effectiveness in handling agricultural data:

- AI-Powered Learning
  - Dexer Natural harnesses the power of AI for continuous learning and improvement over time. Through iterative feedback loops and algorithmic optimization, the system evolves to better understand and interpret the unique nuances of agricultural data.
  - This adaptive learning approach ensures that Dexer Natural remains current and responsive to changing agricultural landscapes and challenges.
- Data Transformation
  - One of Dexer Natural's core functionalities is its ability to seamlessly transform speech entries into structured data. Leveraging advanced natural language processing (NLP) algorithms, the system accurately transcribes spoken inputs into text, ensuring that the collected data is organized and accessible for analysis.
  - This transformation process enhances data usability and facilitates meaningful insights and decision-making.
- High-speed Verification
  - Dexer Natural offers near-instant speech recognition capabilities, enabling error-free data entry at high speeds. The system employs state-of-the-art speech recognition technology to swiftly and accurately transcribe spoken inputs, minimizing the risk of transcription errors and streamlining the data collection process.
  - This high-speed verification ensures efficiency and accuracy in capturing agricultural data, even in dynamic and fast-paced environments.

- Cloud Integration
  - To facilitate seamless data management and accessibility, Dexer Natural securely uploads voice-captured data to the cloud with no lag time. This integration ensures that data is safely stored and readily accessible from any location, enabling real-time collaboration and analysis.
  - By leveraging cloud infrastructure, Dexer Natural offers scalability and flexibility to accommodate large volumes of data, while ensuring data security through encryption and access controls.
- Data Security
  - Dexer Natural prioritizes the safety and precision of uploaded data, implementing robust security measures to safeguard sensitive information. The system employs encryption protocols and access controls to protect data integrity and confidentiality, mitigating the risk of unauthorized access or data breaches.
  - By ensuring stringent data security standards, Dexer Natural instills confidence in users regarding the privacy and reliability of their agricultural data.

Script-Based Data Collection

Unlike Dexer Edge, which required the pre-definition of all parameters and a form-based format for data collection, Dexer Natural simplifies this process significantly. The primary requirement was to create a script that farmers could use as a reference. This script provided a framework for the farmers' inputs, ensuring coverage of all necessary information without the constraints of a rigid form structure. The AI-driven system then autonomously analyzed the spoken inputs based on this script and generated structured, tabulated data. This approach not only simplified the data entry process for farmers but also ensured consistency and comprehensiveness in the collected data. Figure 3.4 presents a snapshot of Dexer Natural. The box at the bottom shows the specific parameters that a farmer needs to talk about in a conversational manner.

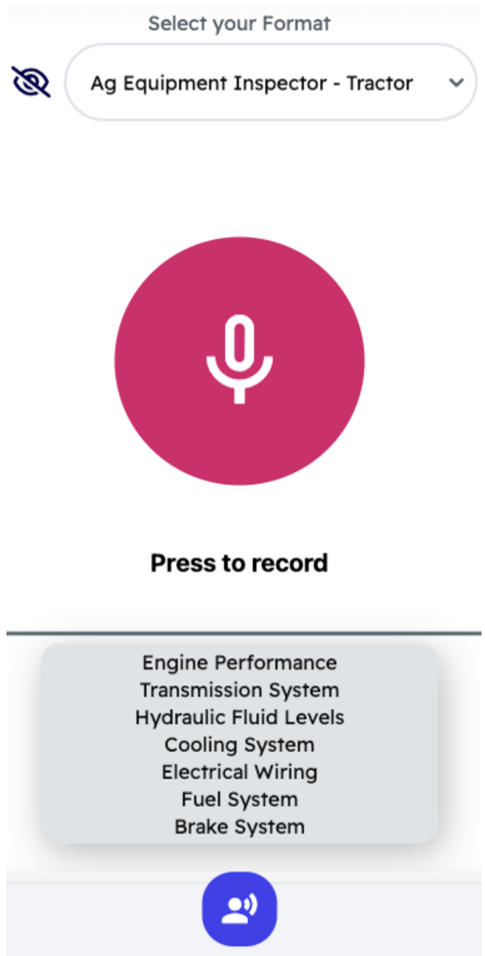

Figure 3.4: *Snapshot of Dexer Natural*

Automated Data Management

One of the significant advantages of Dexer Natural is its automated data management. From the moment a farmer begins recording their feedback, the system continuously saves the data in real time. This eliminates the need for manual saving or data entry, enhancing efficiency and reducing the risk of data loss. The AI handles all aspects of data management automatically, providing a seamless user experience and ensuring that the collected data is always up-to-date and accessible. Figure 3.5 is the automated data analysis generated through AI only by using the farmers' voice feedback.

Name	Britt's farm
Tractor ID	K2 C Gen2 twenty-three horsepower HST OS
Tractor Hours	sixty-five
Implement Type	mid-mount mower
Implement Hours	sixty-five
Tractor Rating 1 to 5	4
Tractor Rating Reason	It is a nice tractor and is working well. However, it doesn't come with any stickers that designate what the levers do. This is especially difficult when numerous people drive the tractor.
Implement Rating 1 to 5	4
Implement Rating Reason	It does a good job of mowing

Figure 3.5: *Automated data analysis*

Overcoming Speech Recognition Challenges

A notable challenge encountered during the implementation of Dexer Natural was the AI's difficulty in accurately recognizing specific words, particularly in noisy environments or with words that are hard to pronounce. To address this, an extensive analysis was conducted to identify words frequently misinterpreted by the AI, which includes words that are non-native to English speakers such as Mahindra, drawbar etc. The solution involved pre-feeding the algorithm with a list of phonetically similar words that could serve as alternatives. This enhancement significantly improved the AI's accuracy in capturing the intended words, making voice-based data collection more reliable and user-friendly.

Expanding Language Support

Given the diverse workforce in farms, it was crucial to broaden the range of sources from which feedback could be collected. Recognizing that many farm workers primarily speak

Spanish, we expanded the application to include Spanish. This expansion significantly increased the inclusivity and diversity of feedback, ensuring that a wide range of perspectives and opinions were captured. By incorporating multilingual support, we enhanced the system's overall efficiency and effectiveness in gathering comprehensive feedback from the farming community.

3.2 Methodology

3.2.1 Workflow

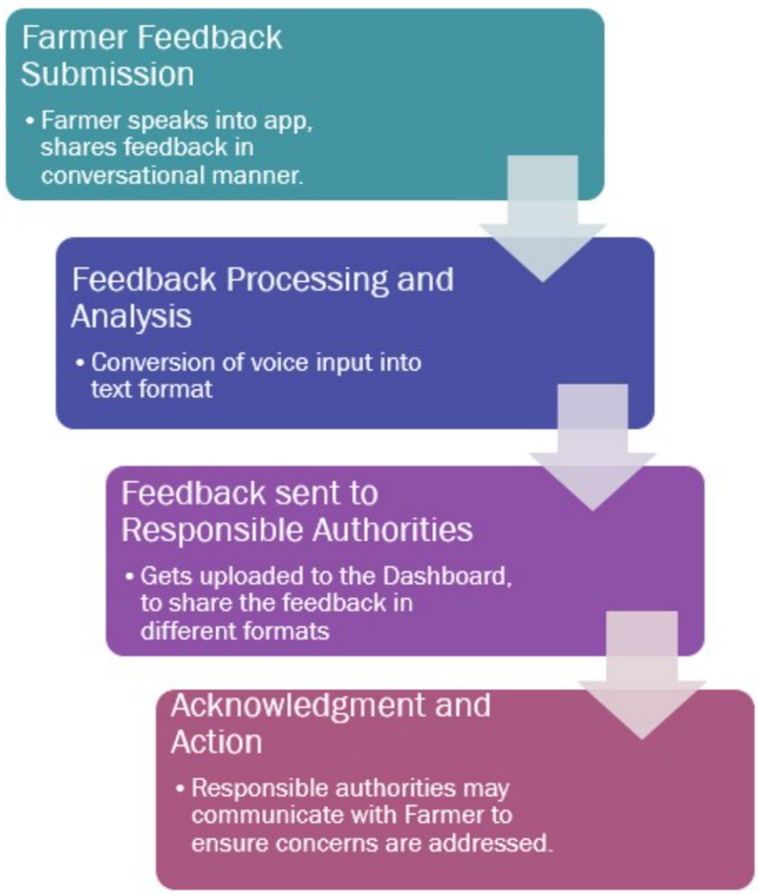

Figure 3.6: *Proposed Methodology*

Figure 3.6 illustrates the overall methodology for this study. With the increasing adoption of digital tools in agriculture, the collection and analysis of farmer feedback have become critical for enhancing agricultural products and services. The Dexer app, which facilitates the collection of feedback from farmers, provides a rich source of data that can be leveraged for advanced analytical techniques. By analyzing two data collection scenarios, we perform a detailed comparative study to identify the most effective data collection engine.

To capitalize on this data, we develop sentiment analysis models to determine the sentiments expressed in the feedback. Sentiment analysis involves evaluating textual data to understand the emotions and opinions of farmers. The accuracy of sentiment analysis models hinges on their ability to correctly identify the relationships between sentiment words and their corresponding targets within the text. By applying these models to the feedback data obtained from the Dexer app, this study aims to extract detailed insights into the sentiments of farmers. These insights are invaluable for understanding the strengths and weaknesses of agricultural products from the farmers' perspectives, ultimately guiding manufacturers in making informed improvements and better meeting the needs of the agricultural community. The integration of advanced sentiment analysis techniques represents a significant step forward in utilizing farmer feedback for the development of more effective and user-centered agricultural solutions.

3.2.2 Comparison of Data Collection Scenarios: Dexer Edge vs. Dexer Natural

In this section, we present a comparative analysis of two distinct data collection scenarios, Dexer Edge and Dexer Natural. Our goal was to determine which method better served our needs by evaluating several key criteria: user accessibility, data accuracy and efficiency, multilingual support, media integration, data management, and analysis capabilities.

- User Accessibility

  Dexer Edge, with its form-based approach, proved to be highly accessible in various environments, including remote farming areas with limited internet connectivity. Farmers could easily input data into predefined forms without requiring real-time internet access. This flexibility was crucial for continuous data collection in the field.

In contrast, Dexer Natural, while offering significant advancements in AI-driven data processing, required a stable internet connection for optimal performance. The AI system's reliance on cloud-based processing meant that farmers could not utilize Dexer Natural effectively in areas with poor or no internet connectivity. This limitation posed a significant drawback in terms of user accessibility, as uninterrupted internet access is not always available in agricultural settings.

- Data Accuracy and Efficiency

  Dexer Natural excelled in data accuracy and efficiency. The AI-driven speech recognition and natural language processing capabilities allowed for near-instantaneous and error-free data entry. By transcribing spoken inputs directly into structured data, Dexer Natural minimized human errors commonly associated with manual data entry such as typographical errors, transposition errors, omission errors, duplication errors etc. Additionally, the continuous learning algorithms enabled the system to improve over time, further enhancing accuracy and efficiency.

  Dexer Edge, while effective in collecting structured data, was more prone to human error during manual data entry. The predefined forms required careful input by users, which could lead to inconsistencies and inaccuracies, especially in high-volume data collection scenarios. However, the simplicity and straightforwardness of the form-based approach provided a reliable, albeit less efficient, method of data collection.

- Multilingual Support

  The ability to support multiple languages is critical in diverse agricultural communities. Dexer Natural's AI capabilities allowed for easy expansion into multiple languages, including Spanish, thereby broadening the range of feedback sources. This multilingual support increased the inclusivity and diversity of the data collected, providing a more comprehensive understanding of the agricultural landscape.

Dexer Edge, on the other hand, required manual adjustments and translations of forms to support multiple languages. This process was time-consuming and less flexible compared to the automated language recognition capabilities of Dexer Natural. Thus, in terms of multilingual support, Dexer Natural demonstrated a clear advantage.

- Media Integration

  Integrating media such as images and videos can significantly enhance data quality by providing visual context. Dexer Natural incorporated media capabilities, allowing farmers to add photos and videos directly within their spoken feedback. This feature facilitated a richer and more detailed data collection process, improving the overall quality of the information gathered.

  Dexer Edge also supported media integration, but the process was more manual and required additional steps for uploading and linking media files to the corresponding data entries. While functional, this method was less seamless compared to the integrated media capabilities of Dexer Natural.

- Data Management and Analysis Dexer Natural's cloud integration enabled seamless data management and real-time analysis. Data was automatically uploaded to the cloud, ensuring it was securely stored and readily accessible for analysis. The AI-powered system could quickly process large volumes of data, providing valuable insights and supporting informed decision-making.

  In comparison, Dexer Edge required manual data uploads and more hands-on management. While it provided a straightforward way to collect and organize data, the lack of real-time analysis and automated management tools made it less efficient for large-scale data processing and timely decision-making.

Figure 3.7 gives an overall comparison between the two data collection scenarios - Dexer Edge and Dexer Natural.

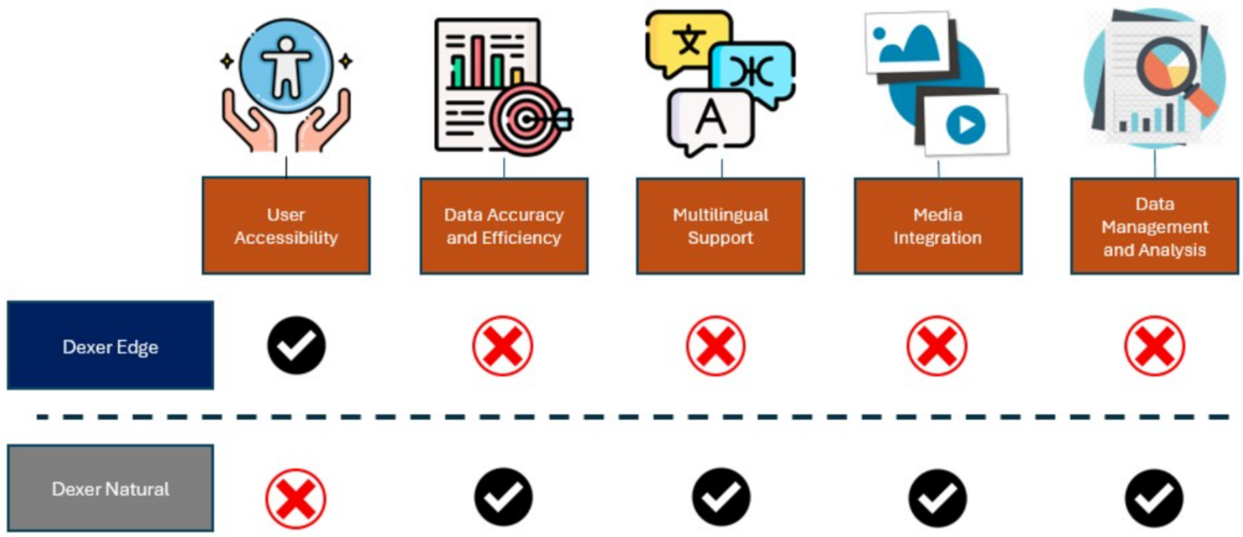

Figure 3.7: *Comparison of Dexer Edge and Dexer Natural*

3.3 Results and Discussions

This section presents and discuss the results of our data collection methodologies. Our findings includes the efficacy of the data collection methods (Dexer Edge vs. Dexer Natural).

1. Dexer Edge Data Collection

   Despite the drawbacks, Dexer Edge's straightforward approach provided a reliable, albeit basic, data collection method. It was evident that while Dexer Edge had its merits, it required significant enhancements to meet the evolving needs of agricultural data collection. Figure 3.8 shows the snapshot of excel containing the reviews collected from Dexer Edge.

2. Dexer Natural Data Collection

   The superior performance of Dexer Natural in these areas made it the preferred choice for ongoing data collection. Its ability to provide high-quality, contextually rich data significantly enhanced the value of the feedback collected from farmers. Figure 3.9 shows the snapshot of excel containing the reviews collected from Dexer Natural.

Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	KB2601	Dom Ne...	5	4	2
Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	KB2601	Dom Bru...	5	4	5
Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	L3901	Dom neu...	5	5	5
Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	MSU40HP	Dom neu...	5	4	4
Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	MSU40HP	MADISO...		4	
Kansas_State_BioAg_Eng	Backhoe	brasa@dexerspeed.	KL3901	MADISO...		4	
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	SUM40HP	Conor	3	3	4
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	KL3901	Doug	5	5	
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	SUM40HP	Doug	4	3	3
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	KL3901	Conor	4	5	
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	SUM40HP	Aden Me...	3	3	
Kansas_State_BioAg_Eng	Backhoe	test1@dexerspeed.c	KL3901	Aden me...		4	

Figure 3.8: *Reviews obtained from Dexer Edge*

1	Capture Date:	Number (Asc.)	Created at time:	UID	Farmer Name	Station	structured_text_csv
3	6/17/24	63	9:35:11 AM	users/NgTXMj3ZXDTyw7TFXsG9ZMDT9Xm1	Justin Mourn. (& group comments)	RED Station 1c	pedal makes you go forward) and suggested reversing them. They also suggested adding arrows to show direction and improving the pedals' return speed to found the air conditioning controls difficult to use due to their placement far to the left and back. They suggested moving them further forward or all the way in controls over buttons which they found more difficult to push and time-consuming.,The group did not like the key fob and would prefer a regular key. They also such as reversing the pedals adding directional arrows to the pedals and improving the pedals' return speed."
4	6/17/24	62	9:33:41 AM	users/zPFZ0mOj16R7scoBJgqFAc9HD1A3	Alan	WHITE Station a	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Rotary Cutter Mower Ratir Reason,PTO System Rating,PTO System Rating Reason,Best Feature,Least Favorite Feature,Overall Thoughts 8,It handled the mower just fine.,5,User woul normal.,7,The engagement seemed abrupt. It might have been a little clank.,2,The big handle is not acceptable compared to other John Deere Kubota and ele engagement lever was too big.,The Mahindra 5145 is probably most adequate for a suburban farmer. User was not able to see any differences in engine perfo 5155 but would be willing to pay more money for more horsepower."
5	6/17/24	61	9:30:00 AM	users/zPFZ0mOj16R7scoBJgqFAc9HD1A3	Alan	RED Station 1c	Cabin Satisfaction Rating,Cabin Satisfaction Reason,Cab Comfort Rating,Cab Comfort Reason,Control Placement Rating,Control Placement Reason,Overall a little tight.,5,It was too tight.,9,It seemed comparable to others.,It is satisfactory."
6	6/17/24	60	9:28:34 AM	users/zPFZ0mOj16R7scoBJgqFAc9HD1A3	Alan	RED Station 1b	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Best Feature,Least Favori B2601,Mahindra 7,It seemed to be okay.,6,I don't feel comfortable with the positioning or the controls.,6,,,,"",Alan rated the engine a 7 the drivability a 6 and th
7	6/17/24	59	9:26:33 AM	sers/zPFZ0mOj16R7scoBJgqFAc9HD1A3	Alan	RED Station 1a	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Best Feature,Least Favori somewhat similar to what I'm familiar with,8,It gets the job done,,,,"
8	6/17/24	58	9:18:22 AM	users/UMjYMhWsm9hqTdWa3H9pswhdhpw2	Hugo	WHITE Station b	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Rotary Cutter Mower Ratir Reason,PTO System Rating,PTO System Rating Reason,Best Feature,Least Favorite Feature,Overall Thoughts 8,It has plenty of power but it does blow black good. It could just improve on the refinement portion.,8,It's very strong. It just needs to be a little bit more smooth.,9,It has plenty of power.,8,It's very easy to g work size.,It needs refinement.,I would own one."
9	6/17/24	57	9:15:47 AM	users/UMjYMhWsm9hqTdWa3H9pswhdhpw2	Hugo	WHITE Station a	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Rotary Cutter Mower Ratir Reason,PTO System Rating,PTO System Rating Reason,Best Feature,Least Favorite Feature,Overall Thoughts 7,Good hay tractor with good power,8,Perforr and capabilities,8,The rotary cutter was not working the tractor much,9,Excellent,Size to power ratio,Limits to horsepower on power-demanding implements,W size. Needs the hydraulics refined would be a class one machine. Willing to pay more money for more horsepower in a tractor this size because the tractor ha: more capable
10	6/17/24	56	9:12:26 AM	users/UMjYMhWsm9hqTdWa3H9pswhdhpw2	Hugo	RED Station 1c	Cabin Satisfaction Rating,Cabin Satisfaction Reason,Cab Comfort Rating,Cab Comfort Reason,Control Placement Rating,Control Placement Reason,Overall spacious compared to last year's model.,8,The cab is good but needs a little refinement on the entrance and exit.,7,Overall it's a good layout.,I enjoy the cab tr one
11	6/17/24	55	9:09:40 AM	users/UMjYMhWsm9hqTdWa3H9pswhdhpw2	Hugo	RED Station 1b	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Best Feature,Least Favori B2601,Mahindra 7,The engine has the horsepower but it could use some fine-tuning on the hydraulics because they could be a little smoother.,7,The drivabilit However the cab is enjoyable although the AC needs fine-tuning.,8,The front loader is very capable just a bit jumpy and it's not as smooth.,The cabin is the be tractors although the AC needs to keep up and there is a preference for dials versus buttons.,The cab access is a bit restricted and needs work.,The cab and t and hydraulics can be fine-tuned the Mahindra would be a winner.,null,The Mahindra is preferred over the Kubota as long as the AC and hydraulics are fine-tu
12	6/17/24	54	9:05:45 AM	users/UMjYMhWsm9hqTdWa3H9pswhdhpw2	Hugo	RED Station 1a	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Best Feature,Least Favori a little bit of horsepower to work the loader but enjoyed the smooth operation,9,Very smooth all around,6,The hydraulics are lacking but the joystick is very erg rocker pedal,Very capable little tractor
13	6/13/24	53	5:01:16 PM	users/InwpdJWbBtXn5stjhV3Jb0qpykt2	Larry	WHITE Station b	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Rotary Cutter Mower Ratir Reason,PTO System Rating,PTO System Rating Reason,Best Feature,Least Favorite Feature,Overall Thoughts 9,It had good power and ran smoothly.,7,The transmission.,9,It was easy to operate.,9,It did a smooth job.,8,It snaps in too fast.,It was powerful.,The positioning of the emergency brake.,They need to reloc different spot.
14	6/13/24	52	4:59:16 PM	users/InwpdJWbBtXn5stjhV3Jb0qpykt2	Larry	WHITE Station a	Engine Rating,Engine Rating Reason,Drivability Rating,Drivability Rating Reason,Front Loader Rating,Front Loader Rating Reason,Rotary Cutter Mower Ratir Reason,PTO System Rating,PTO System Rating Reason,Best Feature,Least Favorite Feature,Overall Thoughts 8,The engine had plenty of power.,8,The trac steering although the shifting was difficult.,7,The hydraulics seemed to work well but the joystick was a little sticky and took some getting used to.,7,The rotary easy to operate.,7,The location of where the PTO shift gears are was not liked.,The tractor was smooth running.,The location of the PTO shift gears.,The Mahi were not many differences noticed between the 5145 and the 5155 and the user would not be willing to pay more money for the horsepower in a tractor this si: between the two horsepowers.
15							Cabin Satisfaction Rating,Cabin Satisfaction Reason,Cab Comfort Rating,Cab Comfort Reason,Control Placement Rating,Control Placement Reason,Overall

All · WHITE Station b · WHITE Station a · RED Station 1c · RED Station 1b · Red Station 1a · KEY Code: Summary · Unified

Figure 3.9: *Reviews obtained from Dexer Natural*

3.4 Conclusion

In this study, we tried to collect farmer feedback on tractors and implements and then process the data in such a way that it can be easily reviewed for any purposes by the tractor companies such as assessing farmer feedbacks on machinery, review on tools etc. We did a comparison on two data collection scenarios using two engines - Dexer Edge and Dexer

Natural. Although they belong to the same parent company, due to numerous features Dexer Natural stood out and was found to be the more efficient one for data collection.

Chapter 4

Comparative analysis of Sentiment Analysis on Transformer Models

4.1 Introduction

The transformation in global communication, driven by the internet, has profoundly reshaped how individuals express themselves, particularly in contexts where significant financial decisions are at stake (Agirre et al., 2014)[15]. As of recent reports by Kepios, a substantial 4.74 billion people, constituting 59.3 percent of the world's population, actively participate in social media. This shift underscores an increasing reliance on user-generated content, which is particularly crucial when substantial sums are at play, such as in the purchase of commodities. This is especially evident in the realm of real-time information platforms, where a profound shift is underway within the agricultural landscape.

Unlike conventional channels, our focus is on unraveling the rich insights woven by farmers themselves—a wellspring of perspectives that intricately influence agricultural dynamics. These platforms serve as vital conduits for farmers to share their stories, challenges, and wisdom. However, navigating this abundance of data requires nuanced and sophisticated tools. Enter sentiment analysis, a time-tested method essential for swiftly uncovering the diverse attitudes and emotions within this distinctive dataset.

Sentiment analysis, also known by various names such as subjective investigation or artificial intelligence of emotions, is nestled within the domain of natural language processing (NLP) (Pontiki et al., 2015)[16]. It becomes a vital lens through which meaningful patterns are extracted from the expansive textual mosaic of farmer-generated content—whether they be anecdotes, feedback, or discussions. This analytical approach allows for a deeper understanding of the nuanced attitudes, viewpoints, and emotions expressed by farmers, thereby providing a holistic understanding of their experiences and aspirations (Peters, et al., 2018)[17].

4.1.1 Transition to Sentiment Analysis from Dexer

Upon collecting the data through Dexer Edge and Dexer Natural, it became evident that the dataset was unique and held the potential to address various agricultural challenges. However, a closer examination revealed that the existing data points were insufficient for reliable analysis. This realization prompted a strategic shift in our approach.

- Expanding the Dataset: Incorporating Car Reviews To enhance the robustness of our dataset, we sought additional sources that could complement the agricultural feedback. We identified car reviews as a suitable parallel due to their similar terminologies and the structure of user feedback. By integrating car reviews data, we aimed to augment our dataset, providing a richer and more comprehensive foundation for analysis.

  The rationale behind this integration was rooted in the linguistic and contextual similarities between car reviews and agricultural feedback. Both domains involve user experiences, feature evaluations, and performance assessments. Thus, car reviews data could be leveraged to enhance our understanding and analysis of agricultural feedback.

- Developing a Comprehensive Analytical Framework

  With a more robust dataset in place, we explored various analytical possibilities. After careful consideration, we identified sentiment analysis as a promising approach to derive actionable insights from the collected data. The goal was to understand the underlying sentiments expressed by farmers in their feedback, particularly in relation to the ratings they assigned to implements and tractors.

- Implementing Sentiment Analysis with Transformers

  Sentiment analysis was chosen because it provided the context needed to interpret farmers' ratings more accurately. Farmers' ratings of implements or tractors often lacked detailed reasoning, making it challenging to derive meaningful insights. By applying sentiment analysis, we aimed to uncover the contextual nuances behind these ratings, providing a deeper understanding of the feedback.

  We employed transformer models, a state-of-the-art natural language processing (NLP) technique, to conduct sentiment analysis. Transformers, known for their ability to capture contextual relationships in text, were ideally suited for this task. They enabled us to analyze the sentiments expressed in farmers' feedback, distinguishing between positive, negative, and neutral sentiments with high accuracy.

- Enhancing Decision-Making with Contextual Insights

  The application of sentiment analysis provided a more nuanced interpretation of the feedback data. This contextual understanding was critical for stakeholders responsible for making decisions based on the feedback. By identifying the sentiments behind farmers' ratings, we could offer more reliable and actionable insights.

  For instance, understanding that a negative rating was due to specific performance issues rather than general dissatisfaction allowed for targeted improvements. Similarly, positive sentiments linked to particular features could be highlighted to inform future development efforts.

4.1.2 Transformer models

In recent years, the development and application of Transformer models have significantly advanced the capabilities of natural language processing. These models, particularly through the utilization of the attention mechanism, have demonstrated outstanding performance.

The attention mechanism allows the model to selectively assign different weights to various parts of the input sequence, thus facilitating the creation of informative embeddings. Specifically, the attention mechanism calculates a weighted sum of the input embeddings, with the weights determined by a learned compatibility function between the query and key embeddings. This capability empowers the model to effectively capture long-range dependencies within the input sequence, resulting in more insightful and contextually relevant representations.

Among these models, BERT (Bidirectional Encoder Representations from Transformers) which was created by Devlin, Chang, Lee & Toutanova, 2018 [12], has gained prominence for its ability to understand the context of a word in search queries. BERT uses bidirectional training of Transformer models to deeply understand the context of words by considering the words that come before and after it. This has made BERT exceptionally powerful in understanding the nuances and context of language, surpassing previous models that only looked at text sequences in a single direction.

Building upon the foundations laid by BERT, its derivative RoBERTa (Robustly optimized BERT approach), created by Liu et al., 2019 [13], has been further optimized and enhanced. RoBERTa is trained on an extensive corpus, enabling it to learn diverse contextual representations more effectively. With fully bidirectional training, RoBERTa enhances its understanding of the contextual relationships between words. It employs dynamic masking during pre-training to encourage a deeper understanding of context and omits the Next Sentence Prediction (NSP) task used in BERT, focusing instead on better capturing sentence relationships. These enhancements allow RoBERTa to demonstrate superior performance on various downstream NLP tasks, making it versatile for fine-tuning applications. The RoBERTa model was specifically designed to address the undertraining issues of the BERT model. By incorporating an additional 160GB of training data, RoBERTa was made more robust and capable of enhanced performance (Liu et al., 2019) [13].

This study aims to develop a robust approach for identifying the opinions and attitudes of farmers towards tractors and implements, leveraging the pre-trained transformer model RoBERTa and BERT. Extensive experiments were conducted, showcasing the state-of-the-art performance of the proposed BERT and RoBERTa-based model. The key contributions of this study include the comparison analysis of BERT and RoBERTa-based model designed to discern farmer sentiments based on ratings (1, 2, 3, 4, 5), contextualized to the farmer's perspective. Our approach distinguishes itself from similar studies for the following reasons:

- **Diverse Training Data:** Our model was trained using two distinct datasets, incorporating feedback obtained in person from farmers and online reviews of tractors and implements. This diversity ensures that the model captures a wide range of perspectives and linguistic nuances.

- **Integration of Pre-trained BERT and RoBERTa:** Our methodology involves amalgamating the knowledge encapsulated in the pre-trained bidirectional transformer BERT and RoBERTa with a deep learning classifier, surpassing the capabilities of traditional machine learning classifiers. This integration leverages the advanced contextual understanding of transformers to achieve superior sentiment classification.

4.1.3 Leveraging BERT and RoBERTa

In the domain of sentiment analysis, particularly within agricultural feedback, various models have been utilized to interpret the sentiments of farmers. Initially, efforts were directed towards rule-based and basic machine learning models. However, these approaches faced significant limitations. The primary challenges included handling the linguistic nuances specific to agriculture and a lack of contextual understanding, both of which are critical for accurate sentiment analysis.

- Limitations of Traditional Models

  Traditional rule-based models struggled with the inherent complexity of agricultural language, often failing to account for the polysemy and ambiguity present in farmers' feedback. Basic machine learning models, such as CNN and RNN, while more advanced, still lacked the depth to fully understand and interpret context-specific language. These shortcomings necessitated the exploration of more sophisticated models capable of addressing these challenges effectively.

- Transition to BERT and Its Derivatives

  Recognizing the need for more advanced models, our focus shifted towards BERT (Bidirectional Encoder Representations from Transformers) and its derivatives. BERT and its variants are designed to overcome issues related to polysemy, ambiguity, and domain-specific language, providing a more nuanced understanding of text. For our specific problem statement, we chose a highly specialized derivative of BERT known as RoBERTa (Robustly optimized BERT approach).

- Advantages of Using RoBERTa

  RoBERTa is trained on an extensive corpus, enabling it to learn diverse contextual representations. Its fully bidirectional training enhances the model's understanding of contextual relationships between words. Unlike BERT, RoBERTa omits the Next Sentence Prediction (NSP) task, allowing it to focus more on capturing the relationships between sentences. Additionally, RoBERTa employs dynamic masking during pre-training, which encourages a deeper understanding of context. These features make RoBERTa superior in performance on various downstream NLP tasks, making it versatile and highly effective for fine-tuning applications such as sentiment analysis in agricultural feedback.

- Methodology for Implementing RoBERTa

  The overall methodology for implementing a RoBERTa model for sentiment analysis is depicted in Figure 4.1. Each steps in the process is explained below:

  1. **Data Preparation and Preprocessing:** The first step involved feeding the farmer feedback data, along with corresponding ratings, into the transformer model. The data was preprocessed to clean and format it appropriately for the model. This preprocessing step ensured that the data was free from noise and ready for tokenization.

2. **Tokenization:** The preprocessed data was then converted into tokens using a RoBERTa-based tokenizer. Tokenization is a crucial step as it transforms the textual data into a format that the model can understand and process.

3. **Model Training and Fine-Tuning:** Once tokenized, the data was used to train the RoBERTa model. This involved fine-tuning the pre-trained RoBERTa on our specific dataset, which included fabricating a neural network tailored to our needs. The fine-tuning process helped adapt RoBERTa to the specific characteristics and nuances of the agricultural feedback data.

4. **Evaluation and Validation:** After training, the model was evaluated on various efficiency parameters to ensure its accuracy and effectiveness. This step involved rigorous testing to validate the model's performance and its ability to accurately interpret sentiments in the feedback.

- Addressing Key Problem Questions

  With the trained RoBERTa model in hand, we sought to answer several key problem questions:

  1. **Variation of Sentiment Across Tractor Models and Implements:** The model helped analyze how sentiment varied among different tractor models and agricultural implements, providing insights into which products received positive or negative feedback.

  2. **Influence of Specific Features on Sentiment:** By examining the feedback, we aimed to identify specific features, such as performance or user experience, that influenced the sentiment expressed by farmers. This analysis highlighted the aspects that mattered most to the users.

  3. **Evolution of Sentiments Over Time:** We also explored how sentiments in farmer feedback evolved over time. Understanding these trends could inform future improvements and developments in agricultural technology and practices.

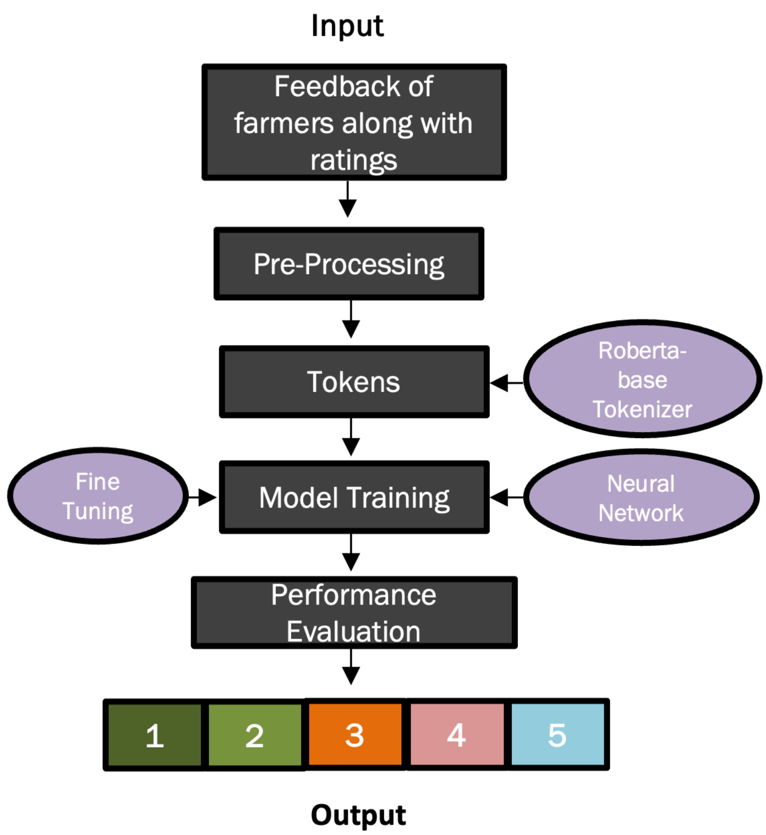

Figure 4.1: *Design Diagram showing the flow of data in a transformer model*

4.2 Methodology

This section outlines the phases of the proposed RoBERTa and BERT for sentiment analysis. Initially, preprocessing steps are applied to the corpus to remove unnecessary tokens or symbols in the text. Following this, a Dataset class is created to define how the text is pre-processed before being sent to the neural network.

Additionally, a Dataloader is defined to feed the data in batches to the neural network for appropriate training and processing. Both Dataset and Dataloader are constructs of the PyTorch library, serving to define and control data pre-processing and its passage to the neural network. Subsequently, the balanced dataset is input into the BERT and RoBERTa model for training and classification.

4.2.1 Project Approach

The purpose of this experiment is to evaluate the classification performance of pre-trained models, specifically BERT and RoBERTa, on multiclass sequence classification tasks using a dataset of farmer feedback. The pre-trained models were fine-tuned to fit the specific characteristics of the farmer feedback dataset, adapting to the nuances of agricultural terminologies and contextual expressions used by farmers. Fine-tuning involved data preprocessing, tokenization, normalization, and handling of special characters or domain-specific terms. Figure 4.2 shows an overall flow of data in this method.

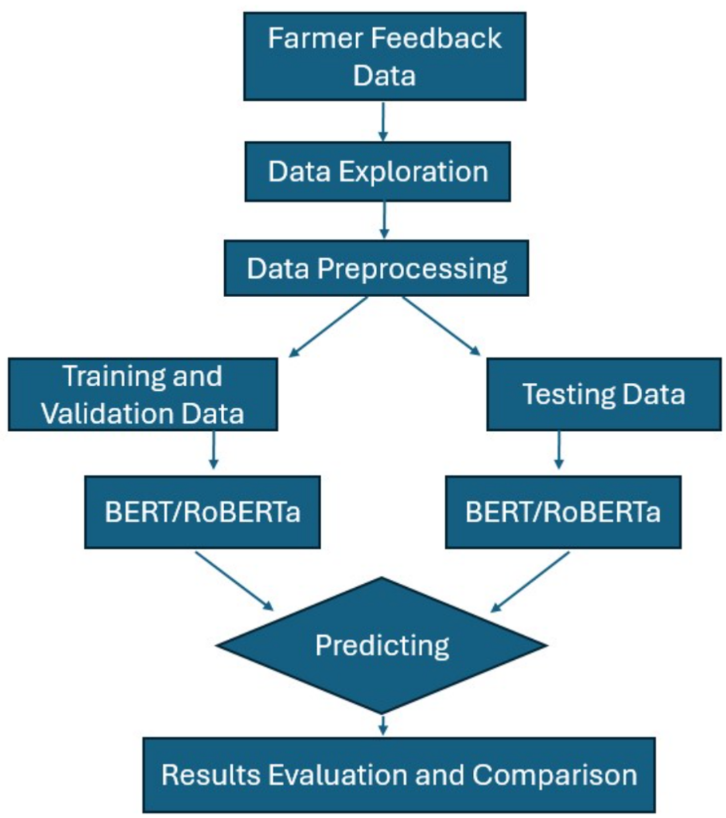

Figure 4.2: *Design Diagram showing the flow of data from pre-processing and passing it to pre-trained models.*

The entire experiment was conducted on Google Colab, a cloud-based platform providing necessary computational resources for large-scale machine learning models. GPUs available in basic laptops typically lack the capacity to handle models like BERT and RoBERTa, which have millions of parameters. Google Colab addresses this limitation by offering a 12GB NVIDIA Tesla K80 GPU and 13GB of RAM, which can be used continuously for up to 12 hours. This setup enabled the efficient execution and fine-tuning of the models, ensuring that the computational demands of the experiment were met effectively.

4.2.2 Dataset Description

The cornerstone of effective sentiment analysis lies in the quality and quantity of the data used. In our study, we utilized a mixed-methods approach to gather comprehensive data, ensuring robustness and reliability in our sentiment analysis results. The primary dataset was collected directly from farmers using the Dexer application on a field day. This method ensured the authenticity and relevance of the data, as it was gathered from the intended end-users of agricultural implements and tractors. A diverse group of farmers was selected to provide a wide range of feedback, ensuring that various perspectives and experiences were captured. Selection criteria included farm size, type of crops grown, and geographical location to cover a broad spectrum of agricultural practices. Farmers were asked to rate their tractors and implements on a predefined scale (e.g., 1 to 5) and provide detailed reviews describing their experiences, challenges, and satisfaction levels. Figure 4.3 shows some of the farmer reviews and ratings collected. These ratings and reviews were recorded in a structured format to facilitate subsequent analysis. A semi-structured interview protocol was employed, allowing for both quantitative ratings and qualitative insights, which enriched the dataset with in-depth personal experiences and contextual details.

Despite these efforts, the initial dataset was insufficient in terms of volume for training robust machine learning models. To address this limitation, we augmented our primary data with secondary data sourced from online tractor reviews. This supplementary data provided additional perspectives and helped in balancing the dataset. Online reviews were carefully selected to ensure they were relevant and comparable to the in-person feedback. This combination of primary and secondary data enhanced the diversity and comprehensiveness of our dataset, making it suitable for rigorous sentiment analysis.

	Review	Rating
0	I am very proud of how well Simplicity made th...	5
1	I bought my tractor used and it was re-powered...	4
2	I got it a while back as a project. it came al...	4
3	The Allis 718h has a 18hp Kohler over head val...	4
4	I have been using my 914 since 1981 mowing law...	5

Figure 4.3: *Farmers' review with ratings*

4.2.3 Data exploration and pre-processing

Data exploration and preprocessing form the foundational steps in any data analysis pipeline, crucial for uncovering patterns, trends, and insights hidden within the dataset. The initial phase of data analysis involves a comprehensive exploration of the dataset to understand its structure, identify any missing or null values, and examine the distribution of various attributes. This step is pivotal as it provides insights into the quality and completeness of the data, guiding subsequent preprocessing efforts. The first thing to check is to verify if the data has any missing or null values, as identifying and handling these gaps is essential to ensure the robustness of the analysis. Techniques such as imputation or deletion of missing values may be employed depending on the extent and nature of the missing data. Text preprocessing is a critical phase in text analytics applications to eliminate noise from the corpus. In this work, various preprocessing steps are executed. Initially, the texts are standardized to lowercase to ensure uniformity. Subsequently, texts that are less relevant in sentiment analysis, including stop words, numbers, punctuation, and special symbols, are removed. Stop words refer to common words such as "a," "an," "the," etc., which are syntactically important but semantically less significant (Narayanaswamy, 2021)[18]. Additionally, stemming is applied to transform words into their root forms. For instance, the word 'collected' is converted into 'collect' after the stemming operation. The BERT model learns by creating an association with other words in the sequence, and if the sequence contains noise, it can adversely affect the model's performance as it does not contribute to the classification purpose. All these noises must be cleared before converting the sequence into tokens by the model tokenizer, as it will convert the unknown noise into new word pieces, which can hinder the model's performance.

4.2.4 Fine tuning BERT and RoBERTa

BERT and RoBERTa models, in their vanilla forms, provide general language representations as they are trained on a broad corpus rather than domain-specific texts. This generalized training allows these models to be versatile across various applications, but to achieve optimal performance on specialized tasks, further fine-tuning is necessary. This fine-tuning process involves adapting the pre-trained models to the specific domain and tasks at hand using the current dataset. The models are equipped with a set of output layers that can be trained further to perform specific NLP tasks, such as sentiment analysis, text classification, or question-answering. During this phase, all the model parameters are fine-tuned together, allowing the model to specialize in the particular data and downstream task being addressed.

BERT and RoBERTa support multiple downstream tasks, including question answering, text labeling, and text classification. In this research, these models are employed for text classification, specifically sentiment analysis. As discussed in previous section, the [CLS] token is embedded into the token sequence of the text. Regardless of whether the task involves a single sentence or paired sentences, the [CLS] token is always positioned at the beginning of the token sequence. The primary function of the [CLS] token is to hold the final classification probability 'h' for the entire sequence. This probability is calculated using the softmax function, which is applied to the output of the classification layer to determine the predicted class. The formula for this calculation is given by:

$$P(c|h) = softmax(Wh) \tag{4.1}$$

where $P(c|h)$ represents the probability of class c given the final hidden h state, and Wh denotes the weight matrix of the classification layer. This approach ensures that the model can effectively capture and classify the sentiments expressed in the text, providing accurate and contextually relevant outputs for the sentiment analysis task.

This $[CLS]$ token is subsequently passed to the final output layer, where the prediction probability for the label 'c' is calculated (Devlin et al., 2018)[12]. In this context, 'W' denotes the parameter matrix for the classification task. Fine-tuning all parameters in the last layer involves maximizing the log-probability of the label 'c'. Devlin et al. (2018) have conducted extensive research and provided a set of hyperparameters suitable for fine-tuning the BERT model:

- **Batch size:** [16, 32]
- **Learning rate:** $[5e^{-5}, 3e^{-5}, 2e^{-5}]$
- **Number of epochs:** [2, 3, 4]

Batch size determines the number of samples processed at a time during model training. Learning rate specifies the extent to which the model's weights are updated during training. The number of epochs defines the full training cycles the model undergoes.

The selection of hyperparameters is highly dependent on the dataset type and size used for training. For large datasets, typically containing over 100,000 rows, fine-tuning hyperparameters does not significantly impact the results. However, for smaller datasets, experimenting with multiple combinations of these hyperparameters is crucial to optimally fit the model to the data during training on downstream tasks.

In this study, the pre-processed dataset consisted of 10,585 rows. Multiple combinations of hyperparameters were tested to determine the optimal settings for both BERT and RoBERTa models. The best combination of hyperparameters was found to be:

- **Batch size:** 16
- **Learning rate:** $5e^{-3}$
- **Number of epochs:** 4

These settings ensured efficient training and high performance of the models on the sentiment analysis task.

4.2.5 Model Implementation

While the pre-training of the RoBERTa model differs significantly from that of the BERT model to enhance performance, RoBERTa remains fundamentally based on the BERT platform. Both models follow a similar process for downstream tasks, from processing input tokens to predicting target classes. Utilizing Huggingface Transformers, as outlined by Wolf et al. (2019), provides an efficient way to import and implement these Transformer-based models. For this study, the 'bert-base-uncased' and 'roberta-base' models were imported from the Huggingface library. The BERT base model consists of 12 encoders and 12 bidirectional self-attention heads, encompassing a total of 110 million parameters. Although RoBERTa maintains the same number of encoders and self-attention layers, the inclusion of additional training data increased its parameters by 15 million, resulting in 125 million parameters for the RoBERTa base model.

The input text must first be tokenized before feeding it into the models. The Huggingface library provides distinct tokenizers for BERT and RoBERTa, each with a unique word-to-token number mapping dictionary and different methods for creating wordpiece tokens. To ensure uniformity, all token sequences are padded to match the length of the longest sequence identified within the dataset, which, in the case of the Farmer Feedback data, was determined to be 261 tokens. During padding, sequences are filled with zeros until they reach the specified length. Additionally, an attention mask is created for each sequence, consisting of an array of zeros and ones; zeros indicate padding tokens, while ones represent real tokens.

The Huggingface transformer library supports both PyTorch and TensorFlow implementations of BERT and RoBERTa models. In this research, PyTorch variants were utilized. Consequently, all input data, including input IDs, target labels, and attention masks, were converted into torch tensor data types before being fed into the models. PyTorch's 'Dataloader' function was employed to load data into the models in batches, based on the specified batch size. This method prevents overloading the model with data, which would otherwise increase the model's size and require larger GPU memory.

Both BERT and RoBERTa models were compiled using the AdamW optimizer and CrossEntropyLoss function, as recommended by Devlin et al. (2018) and Liu et al. (2019). The loss function evaluates the classification model's output by generating probability values between 0 and 1. After training, the models were evaluated using test data, with output probabilities computed via the Softmax function. The models' performance was then assessed based on accuracy, confusion matrix, and classification report. The classification report provided crucial metrics, such as precision, recall, and F1-score, essential for evaluating the model's efficacy in sentiment analysis tasks.

4.2.6 Performance Evaluation

Training, testing, and validation accuracies are fundamental metrics for evaluating the performance of various Transformer-based pre-trained models in this research. These metrics provide insights into how well the model learns from the training data, generalizes to unseen testing data, and maintains its performance consistency. Additionally, precision, recall, and F1-score are employed to compare the models' efficacy on both balanced and imbalanced datasets. These metrics are crucial for understanding the models' ability to handle data with varying class distributions and ensuring that the models are not biased toward more frequent classes.

Accuracy

Accuracy is the measure of correctness of a model. It is usually defined by the number of correct classifications to that of the total amount of classifications. Training accuracy is often used to verify how the model performs for one epoch of training. The test accuracy is the accuracy given by the model after it has been trained completely.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{4.2}$$

Where TP stands for True positives, TN is True Negatives, FP is False Positives and FN stands for False Negatives.

Precision

Precision is defined as the number of positive predictions that were correctly identified by the model. Precision value tells how reliable the model is in predicting the Positive labels. The performance of the model is said to be the best when the value of precision is 1. Lesser the false positives better the precision.

$$Precision = \frac{TP}{(TP + FP)} \tag{4.3}$$

Recall

Recall is defined as the percentage of total relevant results correctly classified by models. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.

$$Recall = \frac{TP}{(TP + FN)} \tag{4.4}$$

F1 score

F1 score is often regarded as the accuracy, but the accuracy of a model largely depends upon the number of True Negatives. But when there is a tangible cost associated with understanding the False Negative and False Positives of a model, a balanced score such as F1 takes into account the weighted average of Precision and Recall in giving the performance metric. F1 score is especially useful when there is an uneven distribution of target labels in the data.

4.3 Results and Discussions

This section presents the results of the sentiment analysis performed on farmers' feedback using both the transformer models - BERT and RoBERTa. We employed a maximum sequence length of 200 tokens for all models.

4.3.1 BERT Model Performance

The BERT model was evaluated for sentiment classification on the farmer feedback data, with fine-tuning applied to optimize its performance. After experimenting with various hyperparameters, the best results were obtained with a batch size of 16. The training process involved careful monitoring of loss plots to ensure a balance between training and validation losses. Table 4.1 shows the hyperparameters used for training the BERT model.

Table 4.1: *BERT Hyperparameters for training*

Hyperparameter	**Optimal Value**
Optimizer	Adam
Epochs	3
Learning Rate	$5e^{-6}$

The loss plot as shown in Figure 4.4 for the BERT model depicts a steady decrease in training loss up to the fourth epoch, beyond which the validation loss starts to rise, indicating the onset of overfitting. To prevent overfitting and ensure the model generalizes well to unseen data, training was terminated after the fourth epoch.

Figure 4.5 presents the confusion matrix for the BERT model. While a high concentration of values along the diagonal is desired for correct classification, the BERT model shows slightly more dispersion compared to the RoBERTa model which is shown in the next section, indicating occasional misclassifications. However, the BERT model still demonstrates a reasonable ability to identify and classify sentiments accurately, though it is not as robust as RoBERTa.

Overall, the BERT model's performance, with well-tuned hyperparameters and strategic

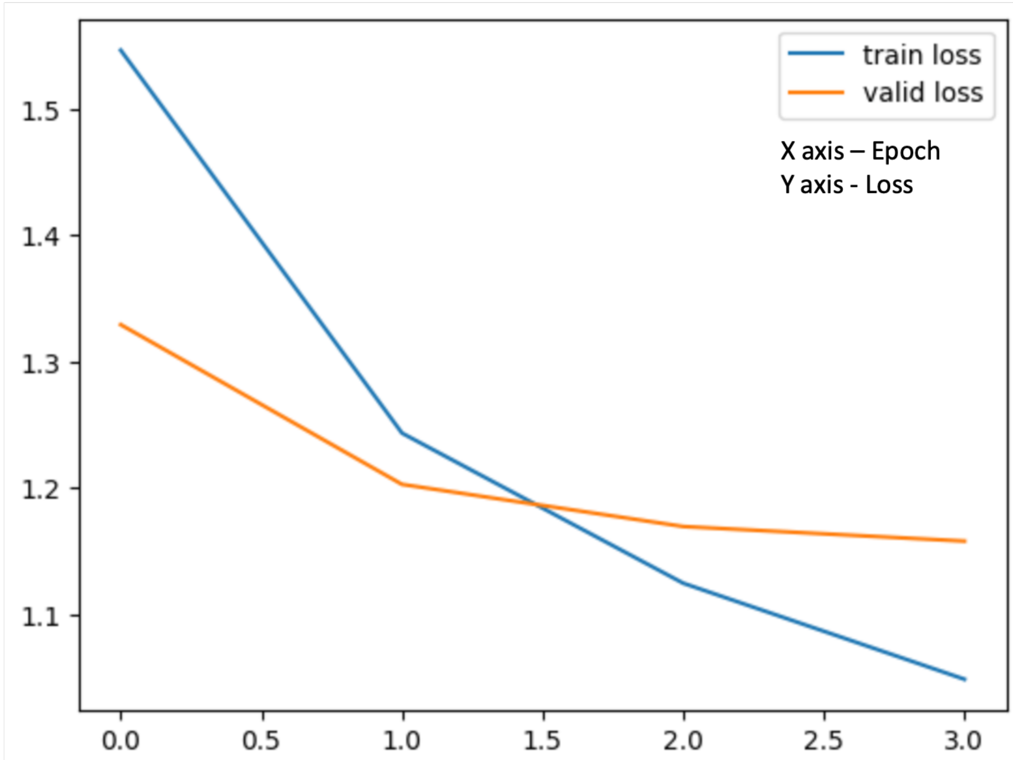

Figure 4.4: *Loss plot of BERT*

early stopping, shows effective sentiment classification in the farmers' feedback dataset. The accuracy and confusion matrix indicate that while BERT is competent in distinguishing between positive, negative, and neutral sentiments, it does not perform as strongly as the RoBERTa model, which is designed to overcome some of BERT's limitations.

4.3.2 RoBERTa Model Performance

We achieved the best performance for the RoBERTa model with a batch size of 8. Table 4.2 shows the hyperparameters used for training the RoBERTa model.

Table 4.2: *RoBERTa Hyperparameters for training*

Hyperparameter	**Optimal Value**
Optimizer	Adam
Epochs	6
Learning Rate	$5e^{-3}$

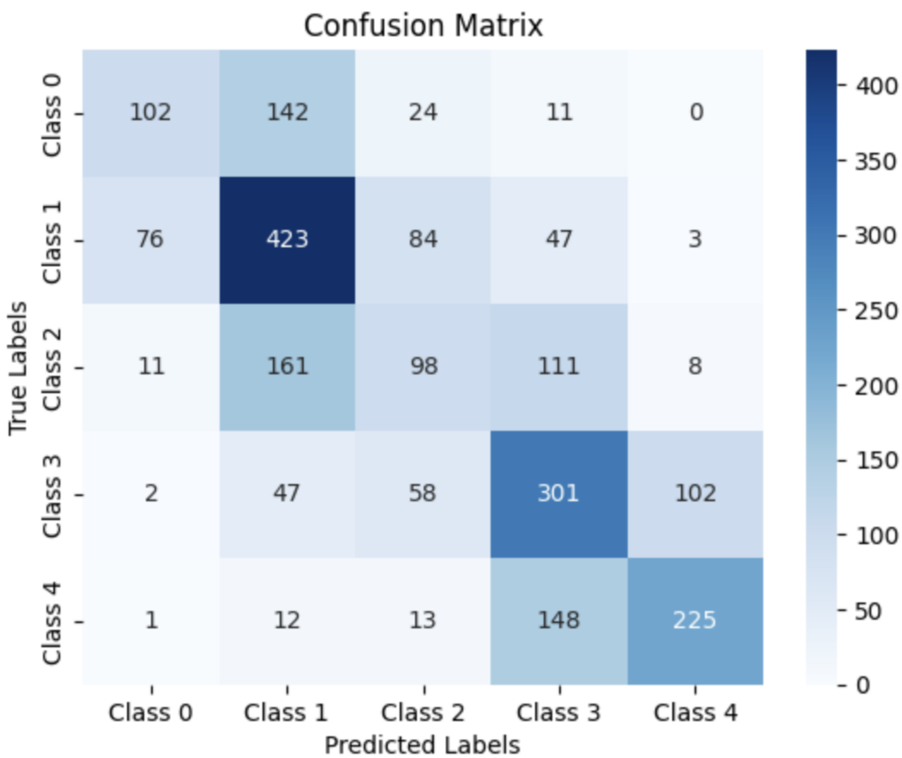

Figure 4.5: *Confusion matrix of BERT*

The associated loss plot shown in Figure 4.6 demonstrates a clear trend of decreasing training loss until the sixth epoch. However, the validation loss begins to increase after this point, indicating potential overfitting. Therefore, we strategically terminated training after the sixth epoch to optimize generalization performance.

Figure 4.7 depicts the confusion matrix for the RoBERTa model. A well-performing sentiment analysis model should exhibit a high concentration of values along the diagonal. This signifies the model's ability to correctly classify sentiment labels (positive, negative, or neutral) for most farmer feedback entries. As evident from the confusion matrix, the RoBERTa model achieves this desired outcome, suggesting a strong capacity for accurate sentiment classification. Table 4.3 gives an overall comparison of the performance parameters of both the models. It can be clearly seen that RoBERTa shows an improved performance when compared to BERT.

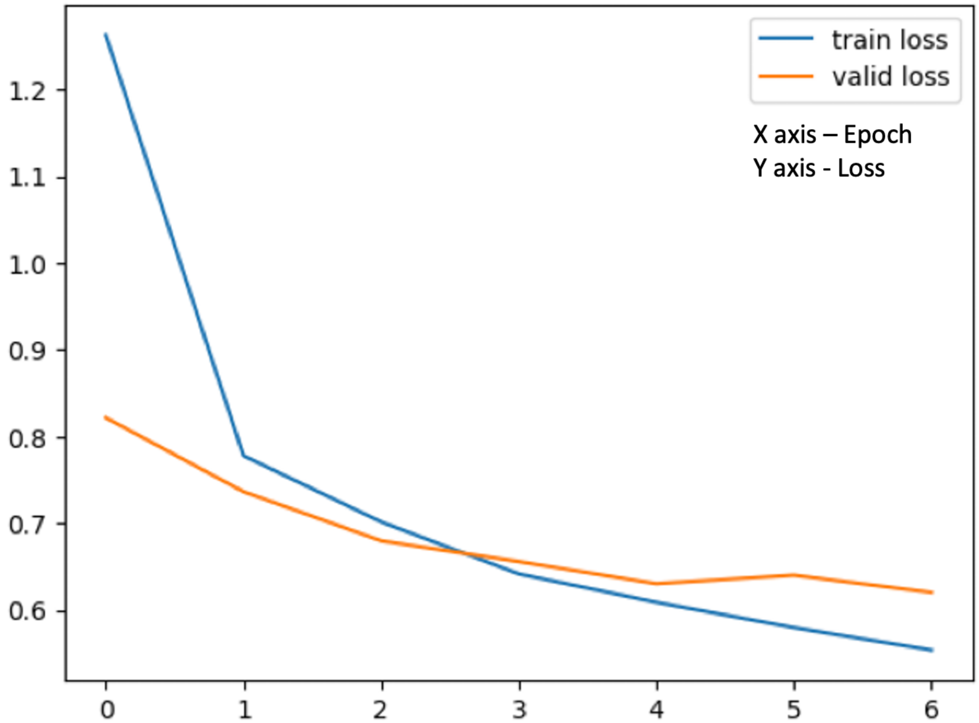

Figure 4.6: *Loss plot of RoBERTa*

Table 4.3: *Comparison of performance parameters*

Performance parameter	**BERT**	**RoBERTa**
Precision score	0.5163	0.6778
Recall score	0.5199	0.7386
F1 score	0.5108	0.7051
Accuracy score	0.5199	0.7386

4.4 Conclusion

Overall, the results demonstrate that the RoBERTa model, with appropriate hyperparameter tuning and early stopping, effectively classifies sentiment in farmers' feedback. The high accuracy and well-distributed confusion matrix indicate the model's robustness in identifying positive, negative, and neutral sentiment within the data.

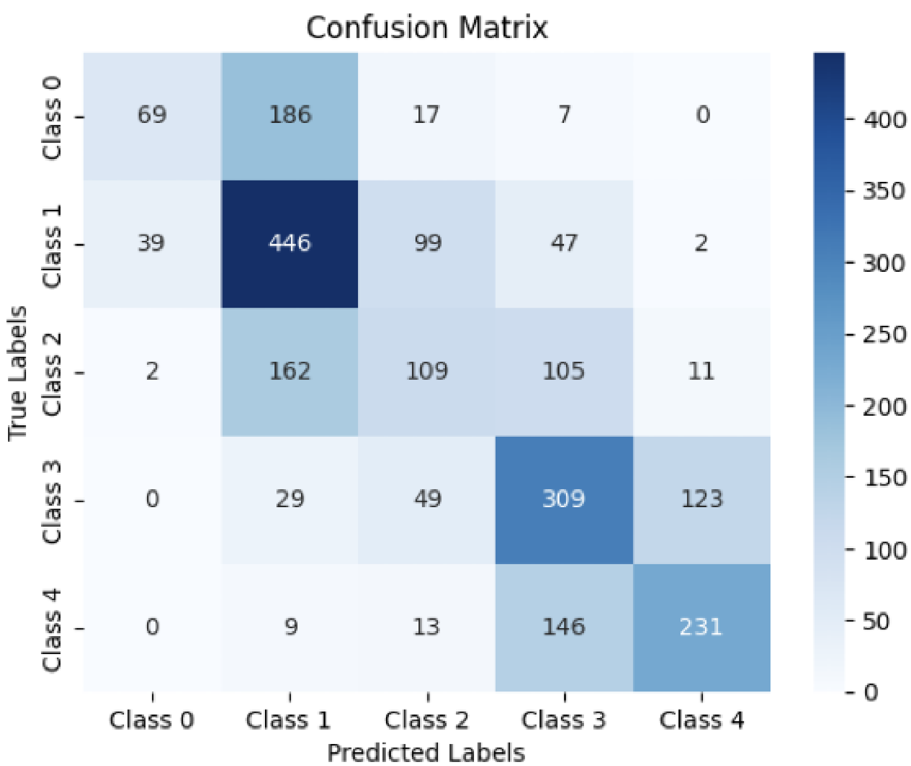

Figure 4.7: *Confusion matrix of RoBERTa*

Chapter 5

Conclusion

5.1 Inferences

The traditional approach to natural language processing (NLP) using techniques such as Word2Vec, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Bidirectional Long Short-Term Memory (BiLSTM) models has inherent limitations in capturing the deeper context of words. These models, while effective to a certain extent, often fall short in understanding the full semantic nuances due to their sequential processing nature and limited contextual awareness.

In contrast, BERT (Bidirectional Encoder Representations from Transformers) represents a significant advancement over these traditional methods. Unlike Word2Vec and similar models, which rely on a restricted context window and process words sequentially, BERT processes the entire sentence simultaneously. This means that when BERT builds a context for a word, it considers not only the words that precede it but also those that follow. This bidirectional approach allows BERT to understand a word's meaning more comprehensively within its context, which is crucial for accurately capturing the subtleties of language.

Moreover, traditional models like Word2Vec generate static word embeddings, meaning a word will have the same vector representation regardless of its context. This can lead to ambiguities when the same word is used in different contexts. For example, the word "bank" in "river bank" and "financial bank" would have the same representation in Word2Vec, despite having different meanings. BERT overcomes this limitation by generating dynamic embeddings that change based on the surrounding words, thereby providing a more accurate representation of word meanings in different contexts.

Building on the strengths of BERT, RoBERTa (Robustly optimized BERT approach) further enhances the capabilities of transformer models by addressing some of the limitations and inefficiencies found in BERT. RoBERTa achieves this through additional training with more extensive data and optimized hyperparameters, resulting in improved performance across various NLP tasks. The modifications in RoBERTa include removing the next sentence prediction objective, training with larger mini-batches, and utilizing longer sequences and dynamic masking patterns. These enhancements enable RoBERTa to capture even more nuanced language patterns and dependencies, making it exceptionally powerful for tasks like sentiment analysis and text classification.

In conclusion, BERT's ability to process all inputs simultaneously and consider the full context of a sentence provides a more nuanced and accurate understanding of language compared to traditional NLP approaches. RoBERTa, building on BERT's foundation, further refines these capabilities with additional training and optimization techniques. The enhanced performance of these models underscores the importance of leveraging advanced transformer-based architectures for complex NLP tasks, ensuring more reliable and precise outcomes in various applications. The integration of BERT and RoBERTa into NLP workflows represents a significant step forward in achieving a deeper and more comprehensive understanding of human language, ultimately leading to more effective and intelligent systems.

5.2 Future Work

Moving forward, future research can explore expanding the data collection process to include a wider range of farmers, potentially encompassing diverse geographic locations or languages. This would enhance the generalizability and robustness of the sentiment analysis model. Additionally, investigating the utilization of more powerful Large Language Models (LLMs) or incorporating image and video data into deep learning algorithms could potentially improve the model's ability to handle complex and nuanced sentiment expressions within farmers' feedback, leading to even more comprehensive and insightful analyses. In conclusion, while this research establishes the effectiveness of sentiment analysis using the RoBERTa model for farmers' feedback, it also emphasizes the importance of continuous improvement. By addressing limitations and exploring new approaches, we can further refine sentiment analysis techniques, ultimately leading to a deeper understanding of farmers' perspectives and valuable insights for agricultural stakeholders.

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