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Sentiment Analysis with Disruptive Technologies in Smart Tilling: A National Framework for Food Supply Chain

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Abstract: Smart Farming (SF) is an emerging technology in the current agricultural landscape. The aim of Smart Farming (Tilling) is to provide tools for various agricultural and tilling operations to improve yield by reducing cost, waste, and required manpower. SF is a data-driven approach that can reduce losses that occur due to extreme weather conditions and calamities. The influx of data from various sensors, and the introduction of information communication technology (ies) (ICTs) in the field of tilling has accelerated the implementation of disruptive technology (ies) (DTs) such as machine learning and big data. Application of these predictive and innovative tools in agriculture is crucial for handling unprecedented conditions such as climate change and the increasing global population. In this study, we review the recent advancements in the field of Smart Tilling, which include novel use cases and projects around the globe. An overview of the challenges associated with the adoption of such technology (ies) in their respective regions is also provided. A brief analysis of the general sentiment towards Smart Tilling technology (ies) is also performed by manually annotating YouTube comments and making use of the pattern library. Preliminary findings of our study indicate that, though there are several barriers to the implementation of SF tools, further re search and innovation can alleviate such risks and ensure sustainability of the food supply. The exploratory sentiment analysis also suggests that most digital users are not well-informed about such technology (ies). Tanzania can be a relevant study reference for such a survey.

Keywords: smart farming; precision tilling; unmanned vehicles; wireless sensor networks; sentiment analysis; Internet of Things (IoT)

1. Introduction

Agriculture is an indispensable field of study, as the continued survival of the human race depends on it. New and updated technology (ies) has been implemented throughout the ages in order to improve agricultural output and sustainability. The world's population is expected to grow to approximately 9.7 billion by the year 2050 [1]. To keep up with this increase in population, food production needs to go up by 70%. However, the resources available to produce the required food output are steadily decreasing due to climate change and an increase in the number of settlements. Water levels are receding, arable lands are shrinking, and the environment is being rapidly degraded. The agricultural manufacturing industry is also one the biggest contributors of greenhouse gases. The strain on the availability of food across the world is predicted to increase drastically with the increase in the world population over the next few decades [2,3]. Agriculture 4.0, or the fourth agricultural revolution, was discussed by the World Government Summit in 2018 in the report titled 'Agriculture 4.0 - The Future of Tilling Technology (ies)' [4]. The report highlights the need for more efficient food production practices that can overcome the increasing food demand in coming years. It would be nearly impossible to keep up with this increase in demand with- out the integration of information and communication technology (ies) (ICTs) and disruptive technology (ies) (DTs) such as remote sensing, Internet of Things (IoT), machine learning, big data, etc., into the agricultural manufacturing industry. Smart Tilling is of great interest to re searchers and scientists as it has yielded great results in reducing the ecological footprint of farm- ing [5], improving production efficiency [6], reducing human labor through unmanned vehicles [7,8], detecting diseases through image processing [9,10], and more.

Precision tilling is an approach that utilizes ICTs to monitor resources such as crops, fields, and animals [11]. It aims to maximize resource usage and crop yield while minimizing associated costs. The agricultural sector consumes a significant amount of resources in the form of water, land, fertilizer, and energy. Precision tilling is concerned with calculating the exact amount of resources required to grow plants and sustain livestock. Smart Tilling, which could be considered an extension of precision tilling, focuses on utilization of data obtained from precision tilling in an intelligent way and making crop production more efficient by predicting crop yield [12,13], reducing wastage of resources, automating tasks [14], and providing agricultural management support [15]. It can also be used to perform soil analysis [16], so that crops of optimal quality can be grown. There have been several calamities in recent years that occurred due to climate change [17]. In light of these calamities, there is great need for smart tilling to assist manage agricultural activities. Due to the various risks and external factors associated with tilling, such as weather extremities and plant diseases, implementation of data-driven predictive tools, which can be used to provide insights into tilling operations such as crop yield, feed intake, weather conditions, soil conditions, etc., is crucial for mitigation [18]. Decisions canthereby be made based on real-time data rather than heuristic, thumb-rule data.

The availability of huge amounts of data from Internet of things (IoT) devices has permited for application of big-data tools. The development of Artificial Intelligence (AI) tools has impacted the efficiency of a number of tasks associated with tilling, suggesting that data-driven agriculture is a good approach to ensure agricultural sustainability. Cli- mate change is predicted to disproportionately impact smallholder farmers [19]. Even a temperature variation of a few degrees will drastically affect smallholder farmers who are not adequately prepared for the situation. A substantial amount of crop losses occur due to weather events, which can be greatly mitigated through predictive weather modeling. This approach can assist farmers navigate the agricultural risks that arise from the unprecedented deterioration of the environment, social and economic changes in the manufacturing industry, and the increase in demand for food production. The availability of big data has the potential to revamp the entire food supply chain [20]. A global connectivity chain in tilling will permit for the use of correctly priced products, better market positioning, and improved means of production. The use of ICT in tilling will provide greater insight and advice on agricul-tural practices to farmers. The increase in visibility that comes with inter-connectivity of the supply chain is also likely to improve the productivity and confidence of farmers in such practices.

Agricultural tasks such as fertilizer and pesticide spraying, crop monitoring, seed planting, etc., can be automated through the use of Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs) [21]. Robots can be trained to autonomously plant saplings and move heavy pots, thus complementing human effort in the agriculturalmanufacturing industry and reducing the farmer's workload [22]. Autonomous vehicles never tire and can work around the clock. They also provide better accuracy and speed to improve the size ofyields. With computer vision, autonomous vehicles can identify if the crops are ripe, ready,and disease-free. Lightweight sensors can be deployed on aerial vehicles to collect detailedinformation about crops and soil parameters through hyper-spectral imaging [23]. Sensors can also be used to map various parameters such as type of land, crop, vegetation index, chlorophyll index, and water index [24]. Drones can assist to create a precision map of a field so that each part can precisely receive the resources it needs [25]. IoT is a major enabling technology (ies) that permits communication between the various sensors installed on the farm. IoT makes use of Wireless Sensor Networks (WSN), which can collect a large amount of data about the environment, crop production, cattle monitoring, and more [26]. Information generated by IoT devices permits farmers to track farm operations and performance, and make informed decisions to improve farm productivity and yield. The massive amounts of data collected from the WSNs can be analyzed through technology (ies) such as big data and deep learning. These technology (ies) provide the added advantages of predictive modeling, real-time decision making, and adaptability to external factors. With the number of smart devices increasing steadily, the implementation of IoT in farms will increase interoperability, decrease losses due to human errors, and provide seamless unification of information. Vertical tilling, which is the practice of growing crops in a vertically stacked layer within a controlled environment for maximum growth, is one way to grow crops independentlyof local soil and climate conditions [27].

The widespread implementation of smart tilling tools faces several limitations and challenges depending on the geographical location of the project. One prominent barrier is the lack of internet connectivity, especially in rural areas. Such technology (ies) is not affordable for everyone. Without a stable internet connection agricultural sensors cannot communicate with each other. The initial cost of installation is high for any SF project, making it especially difficult for smallholder farms to accept the risks. Further, the farmers implementing smart tilling technology (ies) may not fully understand the operation, find the system too complex to use, or may be skeptical about its benefits. Older farmers usually prefer traditional tilling and are unwilling to learn to operate new technology (ies) [28]. The security and privacy of the data generated by sensors is also a concern, as there has to be an accountable party in case of mishandling or misuse [6]. This review paper highlights the current state-of-the-art ICTs and DTs that are applicable to the agricultural sector. Thepractical implementation of these technology (ies) in particular projects across the world has also been covered, along with the limitations of the approaches and their potential to alleviate significant concerns faced by farmers. Exploratory sentiment analysis has also been performed on comments collected from YouTube videos relevant to smart tilling in order to determine public opinion regarding the implementation of these tools. This work aims to serve as a reference and motivation for further re search in the adoption of technological tools in the agricultural manufacturing industry.

2. Motivation

In this study, an in-depth exploration of recent advancements in the field of smart tilling is performed. It has always been a human endeavor to revolutionize agriculture by domesticating animals, planting crops in rotations, using pesticides and fertilizers, etc. The advent of ICTs has brought about the fourth agricultural revolution, or Agriculture 4.0, which focuses on the use of limited resources on targeted areas. As discussed in the previous section, this is achievable with the assist of sophisticated technology (ies) such as unmanned vehicles, satellite imagery, sensors, and more. DTs such as AI have also greatly impacted the agricultural sector by improving efficiency, providing predictive analysis of yield, and mitigating production and market risks. Studies have shown severalbenefits of using smart solutions in tilling practices, such as reduction of necessary manpower, increase in yield, effective management of livestock, monitoring of crops and weather conditions, predictive analysis, and cost reduction. Several initiatives have been undertaken across the world that support the use of precision tilling and smart tilling while also providing insight on the specific limitations that were encountered. It is crucialthat the ever-increasing global food demand is met, as the survival of the human race depends on it.

Smart tilling is capable of providing essential assistance to farmers to ensure sustainable food production. It can assist farmers manage risks by providing specific weather forecasts, yield projections, likelihood of diseases, and more. It can thereby also increase profits for the farmer, as the availability of data on risk assessment and external conditions can permit for optimal cultivation of crops. The motivation for conducting this study is to streamline the current state-of-the-art ICTs and DTs applicable to the tilling sector, analyze components of various smart tilling projects, discuss potential uses of such components, and list the common challenges that face the large-scale adoption of such techniques. The considerations for using smart tilling in different geographical regionsalso needs to be discussed. The general attitude of people towards the adoption of any new technology (ies) is a great indicator of its perceived benefits. To determine the consensus of the opinion on smart tilling, we have performed a surface-level sentiment analysis on comments collected from YouTube channels relevant to smart tilling. Thus, this work can serve as a point of reference for future re search in the area of smart tilling and can assistre searchers explore diverse technology (ies) that are relevant to the topic.

During this exploratory study, we formed the following two hypotheses, each with their respective re search questions for further investigation:

Hypothesis 1. ICTs and DTs can be used in the agricultural sector to make significant improve-ments in several tilling applications. The following re search question was crafted to accept or reject the hypothesis:

1. *What are the state-of-the-art ICTs and DTs currently used in smart tilling?*

Hypothesis 2. There are certain significant challenges to the widespread adoption of smart tilling tools, such as lack of awareness about the topic amongst the general population. The following re search questions are explored in this context:

1. *What are the challenges associated with the widespread adoption of smart tilling tools?*
2. *What are the current opinions and expectations of the digital user with regards to smart tilling?*

For this study, Google Scholar was used to perform exploratory analysis. Specific key- words, such as 'plant disease detection', 'unmanned ground vehicles', 'precision livestock', 'big data', etc., were selected. The searches were performed in the format [technology (ies)][smart tilling]. For example, in order to search for articles that provided an overview of big- data applications in tilling, the search phrase was 'big data smart tilling'. A total of 30 keywords were grouped into six groups to analyze the number of citations for the top five results for each search. We attempted to exclude review papers that covered a few orall of the keywords. The number of citations for the top five results for each keyword is graphed in Figure 1 in six groups. The average number of citations for the top five resultswas calculated. The documents where the number of citations was greater than the average for that keyword were considered for the study.

The rest of this paper is structured as follows: Section 3 covers the various ICTs and DTs, such as big data, IoT, cloud computing, AI, unmanned vehicles, blockchain, and decision support systems, that enable smart tilling initiatives. Re search efforts and projects that utilize such technology (ies) in the agricultural sector are also discussed. Section 4 covers state-of-the-art smart tilling projects that have been launched and completed in the European Union and across the world. A brief overview of user sentiment towards smarttilling technology (ies) is conducted through comments collected from YouTube videos about smart tilling in Section 5, in order to better encapsulate user perception towards such tools. Section 6 highlights the various challenges present in the widespread adoption of precision and smart agricultural practices. In Section 7, we discuss the findings of our study with respect to the two hypotheses formulated, followed by the conclusion in Section 8. The structure of the paper is displayed in Figure 2.

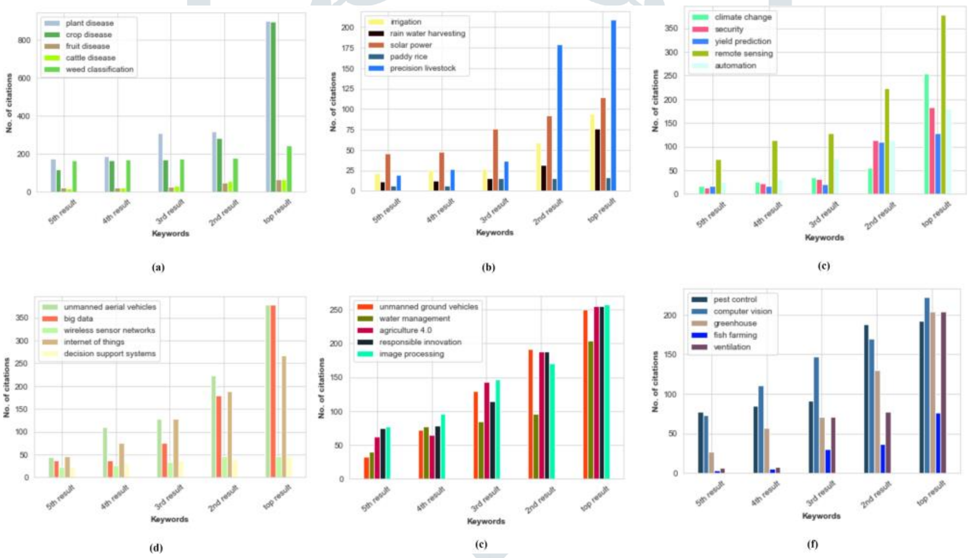

Figure 1. Number of citations per keyword for each of the 6 groups (**a**–**f**) of 5 closely related keywords.The number of citations are compared for the top 5 search results.

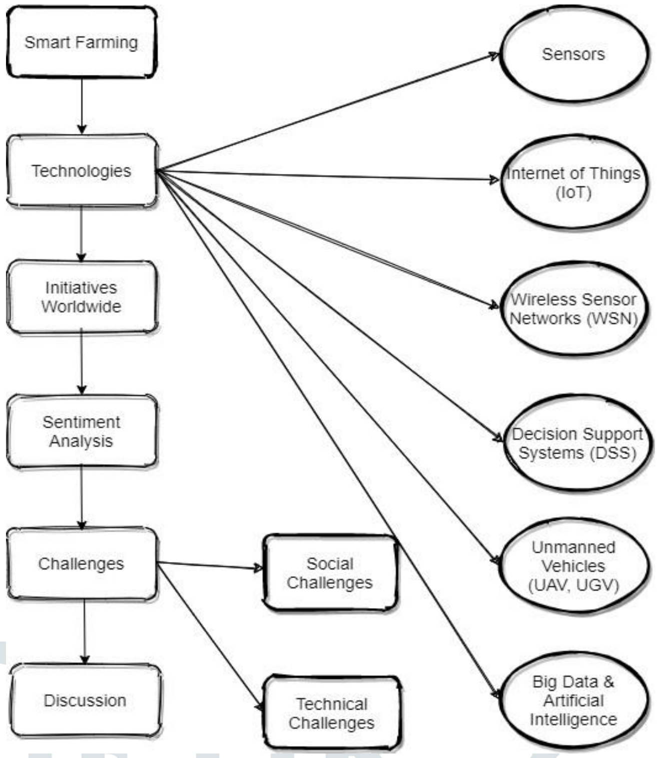

Figure 2. Structure of the paper.

3. Technology

This section provides a thorough discussion of the key technology (ies) that assist in the evolution of smart tilling. These technology (ies) include sensing systems, wireless sensor networks, IoT, unmanned vehicles, decision support systems, blockchain, and more. One or more of these tools has been used in collaboration for smart tilling projects worldwide. The development of new sensors with improved sensitivity has permited for the collectionof higher-quality spatial and temporal data, which can be be analyzed for more timely and efficient decision making. The advancements in remote sensing translate to reducing human time and effort, as less human intervention is required. Over the past few years, UAVs and UGVs have drastically improved in precision and have become more lightweight and cheaper, permiting for their easy adaption on large-scale farms. Wireless sensor networks can assist the seamless functioning of sensors, autonomous vehicles, and decision-supportsystems to impact production at all stages. IoT platforms can permit control of daily farm activities through remote devices. Figure 3 classifies the technology (ies) implemented in smart tilling, along with their most common applications. Table 1 provides a brief description of each technology (ies) along with some related works and applications.

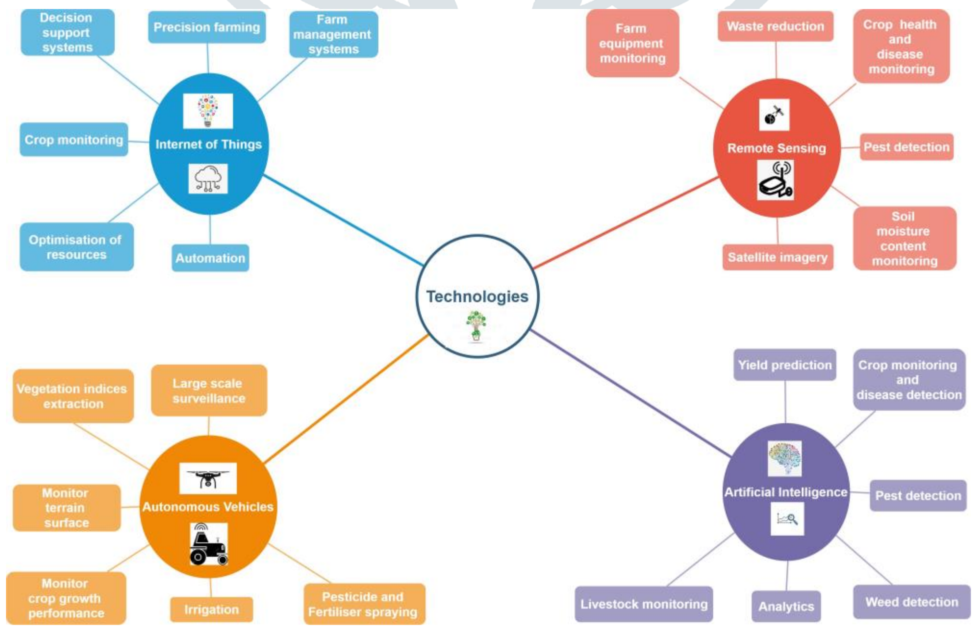

Figure 3. Technology (ies) and applications.

3.1 Sensors

The implementation of ICTs and DTs in tilling is dependent on the availability of wireless connectivity. Remote sensing is crucial for IoT devices to function. Sensors serve as the basic building block in a wireless sensor network (WSN), which then handles the seamless communication between IoT devices. The advancements in sensing technology (ies) translate to the use of additional wavelengths in the light spectrum to remotely monitor crops, manage weeds, capture imagery, and more. Satellites and UAVs are equipped with thermal, visual light (RBG), and near infrared (NIR) cameras to capture multi or hyper- spectral images of the crop field [24]. Hyper-spectral imaging divides light into thousands of smaller bands, which captures a lot of detail. Lightweight, hyper-spectral cameras can be used to monitor crop health, water and nutrient levels, and symptoms of a disease over large areas, which can be difficult to access by other means. The availability of detailed and precise data also permits for spot application of resources and better decision making.

The choice of technology (ies) to be used in a project relies heavily on the available band- width, transmission distance, and energy requirements. Wireless technology (ies) that have been utilized in smart tilling operations over the years include Bluetooth Low Energy (BLE), ZigBee, WiFi, 3G/4G/5G, LoRa, and more. Cellular networks (3G/4G/5G) serve the purpose of aggregating data from various sensors in a smart tilling environment. Bluetooth Low Energy (BLE) provides coverage of 100 m and consumes less power than Bluetooth. It can be implemented in systems for livestock positioning [52], greenhouse monitoring [30], and more. BLE is not suitable for transferring large amounts of data [53].

ZigBee is a WSN protocol that provides a smaller coverage area and low energy con- sumption. It can be used for scenarios such as solar power monitoring [54], greenhouse monitoring, etc. WiFi is beneficial where high bandwidth and large amounts of data trans- fer is required. Cellular 3G/4G/5G networks offer wide coverage and low latency, but they drive up the cost and power consumption. LoRa can cover an area of 20 km and consumes less energy. Specialized sensors have been introduced for tasks such as pest identification and control, plant health monitoring, resource level monitoring, etc. Bug detection and classification can be performed using acoustic sensing devices and cameras, which capture factors such flight behavior and humming sound [55]. Similarly, parasite detection was performed in study [56] using a spectral sensor that measures light waves. The difference in the reflected light pattern can be an indicator of infestation in the plant.

López et al. [57] propose an autonomous monitoring system that uses a low-cost image sensor for visually inspecting bug traps deployed across the field. Bioacoustic sensors have also been deployed to detect red palm weevil infestation in palm trees [58]. Wireless sensors can be installed on leaves to monitor parameters such as humidity, water content, temperature, etc., to estimate the plant's health and required amount of resources [59]. The growth rate of the plant stem and trunk can also be used to determine its health. Various sensors, such as the stem micro variation sensors, sap flow relative rate sensors, stem flux relative rate sensors, auxanometers, and trunk dendrometer, are used for this purpose [60]. Environmental factors such as atmospheric pressure, solar radiation, wind speed, rainfall, temperature, and humidity can also be measured by wind speed and direction sensors, ambient seismic energy sensors, precipitation sensors, etc. [61]. Global navigation satellite systems (GNSS) can assist increase efficiency in smart dairy tilling. Smart collars can be worn by cows and can be used to collect data on the health and well-being of livestock [29]. Farmers can program GPS collar trackers to keep cattle in a certain area. The cattle can then be sent to autonomous milking robots when their udders are full. The amount and quality of milk is then analyzed by the robots. Virtual fences can also prevent cattle from getting hurt on electric fencing and permit for rotational grazing [62].

Table 1. Overview of ICTs in smart tilling.

Technology	Description	Applications
Sensors	A Sensor is a device that detects changes in the physical environment and records this information for future analysis.	Smart collars for monitoring cattle well-being [29]; Hyperspectral imaging of crop field [24]; Greenhouse monitoring [30]
IoT platforms	IoT is a network of physical objects which share information across the internet.	Real-time monitoring and management system for wheat diseases, pests and weed [31]; IoT platforms using sensors to measure and monitor humidity using the NETPIE protocol [32]; Monitoring health status of dairy cows using IoT and wireless body area networks (WBANs) using LoRa [33]; AgriTech – framework of optimising resources using IoT-based smart farming [36]; An IoT-based greenhouse monitoring system with Micaz motes [37]; IoT-based agricultural stick integrated with Arduino technology and solar technology for temperature and moisture monitoring [37]
Decision support systems	DSS is an information system that assists in operational decision making by providing additional predictive insights.	DSS for automatic climate control and minimising diseases for greenhouse tomatoes [38]; AfriPrediction-LoRa IoT technology-based support system using ARIMA prediction model [39]; AgroDSS-cloud-based DSS for farm management [40]; Web-based decision support system capable for supporting farmers in selecting appropriate alternative crops [41]
Cloud/ edge computing	Cloud computing is the online delivery of hosted services, such as software, storage, and computation power. Fog/ edge computing is a decentralised computing architecture between the cloud and connected peripheral devices that allows computation and storage closer to the edge devices.	Cloud-computing-based system for early detection of borer insects in tomatoes [42]; cloud-computing-enabled spatial-temporal cyber-physical infrastructure (CESCI) for soil monitoring [43]; Cloud-based farm management system (FMS) developed within FIWARE [44]; IoT-based smart

		farming system built upon FIWARE for fruit quality control [45]; IoT platform based on edge and cloud computing for soil-less culture needs in greenhouses [46]; Fog-computing-based framework designed to provide a complete farming ecosystem [47]
Blockchain	A distributed, immutable ledger that keepers a record of all transactions of digital assets over a network.	Smart contract-based authentication scheme [48]; model ICT e-agriculture system with a blockchain infrastructure and evaluation tool [49]; Blockchain-based secure smart greenhouse farming [50]; Ecological food traceability system based on blockchain and IoT technologies [51]

3.2 IoT Platforms

IoT can enable devices and sensors to collect data about physical parameters of a farm. The functionalities provided by IoT, such as smart processing of data and real-time communication between devices, enable it to optimize agricultural practices [63]. IoT blends the usage of physical devices such as actuators and sensors with a WSN to permit forseamless communication [26]. Sensors can serve as the peripheral devices that can gather information over a WSN which can then be analyzed with an IoT platform. There are currently several commercially available IoT platforms that aim to greatly reduce manuallabor. They are utilized in various functions of crop monitoring. Zhang et al. [31] proposea monitoring system for wheat diseases, pests, and weed.

The system collects data from IoT terminals and attempts real-time monitoring and management of crops. Lee et al. [64] implement a predictive system for effective pest control and proper utilization of pesticides and fungicides. Correlation is calculated between the pests and weather data relevant to the control of pests. Chieochan et al. [32] implement IoT sensors to monitor the humidity of a mushroom farm. The system controls sprinklers and fog pumps and provides push notifications to the user. Benaissa et al. [33] implement Wireless Body Area Networks(WBANs) in conjunction with IoT to monitor the health of dairy cows. Timely detection ofhealth issues in the cattle is a costly and challenging task that was automated in the studythrough the use of a Long-Range (LoRa) off-body wireless channel and IoT. Garcia et al. [65] implement WSNs to monitor the presence of pests such as snails. The system is also capable of predictive analysis based on environmental factors such as temperature and humidity.

Giri et al. [34] introduce an automation framework called AgriTech for adequate uti- lization of water, fertilizer, and pesticides. AgriTech permits the farmer to monitor the field and perform actions such as spraying through the use of a mobile device. Kodali et al. [66]present the model of an IoT-based smart greenhouse that automatically carries out irri-gation, temperature and air humidity control, and water management with the assist of sensors. In the study done by Na et al. [35], an IoT-based remote monitoring system is implemented to monitor soil characteristics such as pH, temperature, and moisture content using a DS18B20 sensor. Accurate measurement of such parameters can enable better analysis and decisions regarding fertilizer usage and crops sown.

Kamilaris et al. [36] introduce Agri-IoT, a framework for analyzing real-time data streams from heterogeneoussensors that also supports decision making. It supports integration for data streams from multiple domains, data analytics, and interoperability for smart tilling applications.Akkas et al. [37] implement a prototype of a wireless sensor network made up of MicaZ motes that monitor environmental variables such as temperature, light, pressure, and humidity in a greenhouse. The study highlights the advantages of implementing a WSN over traditional cabling within an IoT platform, such as costs, vulnerability, and inability to relocate the wiring system. Nayyar and Puri [67] propose the use of an IoT-based agricul-tural stick integrated with Arduino technology (ies) and Solar technology (ies) to capture live data on physical factors such as temperature and soil moisture. The system provided accuracyof 98% in live feeds when tested on live agricultural fields.

3.3 Decision Support Systems (DSS)

Decision support systems (DSSs) add value to the smooth functioning of tilling practices by providing support to farmers, guiding them to correct information, assist- ing in decision making, and laying out the best course of action for a given scenario. The farm-wide availability of production rules and expertise can drastically improve effi-ciency. Canadas et al. [38] propose a real-time decision support system implemented for greenhouse tomatoes that facilitates better decision making by identifying sensor faults, maintaining climate variables, and performing disease identification on crops. The study highlights the effectiveness of the DSS in climate control and minimizing crop wastage due to diseases. Taylor et al. [68] perform a case study on web of things that highlights other useful applications of support systems such as environmental and livestock moni- toring. Dos Santons et al. [39] present AgriPrediction, an IoT-based support system that utilizes LoRa wireless network range system and the ARIMA predictive model to better manage crop dysfunctions.

The system presents promising results, and is also shown to be applicable in rural areas with sparse connectivity. Kukar et al. [40] present AgroDSS,a novel cloud-based decision support system that permits farmers to perform predictive analysis on their own farm data. The system was implemented to study pest population and provide a better understanding of interdependencies of various parameters in a sim- ulated environment. The study done by Antonopoulou et al. [41] provides an approach for continued sustainability by permiting farmers to select alternate crops for a region. The system can be accessed through mobile devices to increase adoptability amongst farmers,and supports the farmer throughout the cultivation process. Thakare et al. [69] provide a DSS for remote monitoring that integrates smart sensing and smart irrigation systems to monitor parameters such as temperature, moisture content, and efficient water use. The study emphasizes the importance of smart tilling with hydroponics, which permits tilling in unsuitable soil and water conditions.

3.4 Unmanned Vehicles

The advancement in robotics has led to the development of autonomous vehicles, which are used extensively in tilling for mechanical weeding, fertilizer spraying, and harvesting. Unmanned vehicles have shown to decrease human labor, improve productiv-ity, reduce costs, and increase accuracy of measurements. They could be further classified into UAVs and UGVs. UAVs are aircraft embedded with wireless sensors, transmitters, and/or cameras that can function autonomously or be controlled remotely. UGVs, on the other hand, are autonomous machines that operate while in contact with the ground. The use of lightweight cameras with autonomous aerial vehicles can permit for remote monitoring of crops, which can permit for better decision making. Bareth et al. [70]

per- formed a study to examine the usability of UAV-based multi-temporal crop surface models for estimating plant height, estimating the biomass through height measurement, and combining vegetation indices for more accurate estimation. The results obtained from field experiments imply that UAV-based RGB imaging can provide accurate modeling of physical parameters of the plant.

The review study done by Roldan et al. [71] highlights the advancement of robots in smart tilling for automation of labor-intensive tasks such as planting, harvesting, monitoring, inspection, and treating crops. Unmanned vehicles are able to collect information about the environment and navigate it by using machine vision systems. They implement Global Navigation Satellite System (GNSS) technology (ies) [72] to navigate precisely. UAVs provide an added advantage for remote sensing in the form of timely control and high spatial ground resolution. Remote imaging can capture several characteristics through different types of cameras, such as multispectral, thermal, and high spatial resolution RGB camera, as demonstrated in the study done by Matese et al. [73] to measure intra-vineyard variability and leaf temperature and to perform analysis of missing plants. UAVs possess the potential to obtain high spatial resolution imagery without being too affected by weather conditions.

Lu et al. [74] perform species classification in tall grassland with the use of high spatial resolution imagery obtained from a UAV, and show that the method obtains higher accuracy than other data from satellites. Tripicchio et al. [75] present a novel implementation of anRGB-D sensor integrated with UAVs to differentiate between different plowing techniques used on a field. The system provides the functionality of computer vision, navigation, and data analysis and was shown to be a feasible technique for determination of soil characteristics. Moribe et al. [76] provide an effective and synchronized technique for measuring leaf temperature. Infrared thermometers attached to drones and sensor nodesintegrate seamlessly with the WSN.

Lottes et al. [77] propose a system that utilizes a UAV to detect vegetation, such as sugar beets, and performs feature extraction and maps the distribution of weeds and crops. UAVs provide an autonomous solution for monitoring large areas of agricultural land covering crops, livestock, and more. Unmanned vehicles function through the use of technology (ies) such as robotics, IoT, remote sensing, and big data, and can automate labor-intensive tasks such as spraying, data collection, water management, weed mapping, irrigation, fertilization, crop monitoring and management, and field-level phenotyping.

3.5 Cloud/Edge Computing

Given the vast amount of incoming data from various sources, a centralized approachto storing and managing large amounts of data is essential. A cloud-based architecture can permit for the necessary computation power to analyze the plethora of data obtained from the different types of sensors installed on a farm. Cloud computing facilitates flexiblestorage and availability of data and resources, making them suitable for real-time implemen- tation. Rupanagudi et al. [42] propose a novel solution to pest control in tomatoes by crop monitoring using video processing, cloud computing, and robotics. Zhou et al. [43] present a cloud-computing-enabled spatio–temporal cyber–physical infrastructure (CESCI) to per-form comprehensive surface soil moisture monitoring, which can assist reduce costs, increase agricultural productivity, and boost farmers' net income.

FIWARE is an open-sourced cloud platform that has shown potential in many smart tilling applications. Kaloxylos et al. [44] present a cloud-based farm management system that utilizes the FIWARE architecture and was shown to be acceptable by farmers during evaluation. Corista et al. [45] introduce an IoT-based smart tilling system built upon FIWARE that aims to control fruit quality during the entire fruit production chain. The system is developed using the vf-OS (virtual factory Operating System) platform, which integrates various applications and permits external producers and consumers to interact.

Another IoT platform based on cloud and edge computing is proposed by Zamora et al. [46] and works in three tiers: the local plane collects data on crops, the edge plane monitors and manages the main precision agriculture (PA) tasks, and the cloud platform maintains records and performs data analytics. Fog computing, also called edge computing, is a decentralized computing architecture between the cloud and connected pe- ripheral devices and aims to enhance speed and performance [78]. Edge computing systems provide a decentralized approach to automation of tasks by using pre-loaded field data from edge locations [79]. Thus, fog computing is a promising architecture for smart tilling solutions, since it provides low latency and increased reliability for support systems [80].

In case of real-time operational decision making, time is of the essence. Malik et al. [47] introduce a simulation platform that leverages fog computing to permit users to under- stand sensor deployment and data collection in a complete tilling ecosystem. Thus, a cloud platform is essential if real-time analysis is to be performed. Use of additional data-driven approaches can be invaluable depending on the application. Cloud computing architecture can be used to manipulate large amounts of heterogeneous data arising fromseveral sources. It can provide the necessary storage and computation resources, making it complementary to big data tools.

3.6 Blockchain

Blockchain technology (ies) provides new modes of interaction between parties in a supply chain. It is a distributed, immutable ledger that keeps a record of all transactions of digital assets over a network. It also has the capacity to improve food safety by providing traceabil- ity for purchased food products and monitoring for contamination. In order to avoid bias in the data collected from ICT and DT devices, it is important that data manipulation is made difficult or impossible. The addition of a new record in a blockchain requires verification from a peer-to-peer network, ensuring its legitimacy. Similarly, the majority should agree while making changes to records, making it difficult for unauthorized individuals to alter the data. Thus, blockchain-based technology (ies) for smart tilling ensure that the data is correct, transparent, and traceable. In conjunction with smart contracts, which are protocols that are activated without human intervention when the terms of an agreement are met, blockchain technology (ies) can ensure timely payments [81].

Vangala et al. [48] propose an authenticated key agreement mechanism for smart tilling that is based on smart contracts. The system is shown to provide more security and functionality than other authentication protocols. Patil et al. [50] present a security framework that combines blockchain technol-ogy with IoT devices and permits sharing of a digital ledger of transactions among the nodes on an IoT network. Lin et al. [51] introduce an ecological food traceability system that incorporates blockchain technology (ies) and IoT and aims to improve food safety while also establishing trust between the parties involved. The use of smart contracts is also consid- ered for the timely management of problems in the system. An ICT and DT e-agriculturalsystem with blockchain technology (ies) that distributes water quality data over a network is proposed by Lin et al. [49].

They also present an evaluation tool that can be used to determine the specific requirements and suitability of this technology (ies). A simulated model of blockchain technology (ies) is proposed by Widi Widayat et al. [82] and can be implemented in a smart tilling environment. The parties in a smart tilling system, namely farmers, food suppliers, and customers, are connected to a global blockchain network and appear as a node account in the smart contract. Another potential application of blockchain tech-nology is for providing agricultural insurance. Nguyen et al. [83] present a smart contract developed on NEO to provide drought-based crop insurance. This could be invaluable to farmers who work in extreme weather conditions, as it can reduce their damages and vulnerability while also avoiding excess evaluation costs.

3.7 Big Data and Artificial Intelligence

IoT devices and sensors capture various types of data from all over the field that canthen be analyzed through big data tools. Big data refers to larger and more complex datasets that consist of a greater variety of data from multiple data sources and can also be mined for opinions and information [84]. Data modeling techniques such as machine learning and deep learning can assist enhance the entire food production cycle by performing predictive analysis, providing real-time decision making, and refining the business model of the farmto cut loses. AI is a re search sub-field of computer science that utilizes robust datasets to solve problems by performing classification or predictions based on the input data [85]. Machine learning is a sub-field of AI that permits models to learn from experience withoutbeing explicitly programmed.

Deep learning is a sub-field of machine learning that furthereliminates some of the human intervention required in training by automating feature extraction from larger datasets [86]. Currently, there are also several types of state-of-the- art conversational systems being used to assist farmers in agricultural operations [87]. Table 2 summarizes some notable re search works in smart tilling that have performed image processing using Convolutional Neural Networks (CNNs). CNNs are a class of Artificial Neural Networks (ANNs) that are used to perform classification tasks on images by adjusting learnable weights and biases [88]. Table 3 provides a summary of various studies that have utilized other AI models in smart tilling, along with their respective outcomes.

AI can assist reduce resource wastage through monitoring and predictive modeling. Varghese and Sharma [89] propose a hardware-based system that assists monitor factors such as moisture content in soil, humidity, and atmospheric conditions. The system also determines the appropriate crops for given soil and environmental conditions through the use of IoT and machine learning. Arvindan et al. [90] introduce an automated irrigation system that measures moisture content in the soil and provides remote control through an Android smart phone. This can assist with the sustainable and automatic tilling of certain crops that require different degrees of irrigation depending on their growth stage. Khaki et al. [91] introduce WheatNet, which is a CNN that collects field observational data,such as wheat head counts.

The system achieves a Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of 3.85 and 5.19, respectively, in the wheat head counting taskwith fewer parameters, implying that the approach is robust and crucial for observation and decision making. Deep learning algorithms are used extensively to reduce crop wastage and optimize crop yield. The development of systems for accurate prediction of crop yieldis essential, especially in developing countries, as it can secure food availability, prevent famine, and provide further assistance to the sustainable development of agriculture. Crop yield can depend on several factors, such as genotype, environment, etc. Wang et al. [12] present a deep-learning-based system for predicting soybean crop yields based on data collected from remote sensing.

Long Short-Term Memory (LSTM) cells were trained and tested on 4 years of Argentinian soybean harvest data. The model's transferability was then tested by using soybean harvest results from Brazil. Khaki et al. [13] implemented Deep Neural Networks (DNNs) for yield prediction of maize. The dataset consisted of the genotype and yield performance of 2267 maize hybrids. The best-performing model provided an RMSE of 12% of the average yield and 50% of the standard deviation for the validation dataset in imperfect weather conditions. Alfred et al. [92] provide a survey of the implementation of big data and machine learn- ing on paddy rice production in the Asia–Pacific region. The integration of sensors, satellites, and drones complements machine learning tools in improving productivity. Machine learn- ing tools utilize the big data collected from these devices for estimating rice yield [93,94], monitoring growth [94], and providing a smart irrigation system [95]. Kiruthika et al. [96] propose a system to detect paddy rice crop diseases such as leaf blast disease, brown spotdisease, and bacterial blight disease.

A Gray-Level Co-occurrence Matrix (GLCM) is used to recognize disease from the input image; two classifiers are used for recognition: ANN and Support Vector Machine (SVM). ANN performs better than SVM, with a precision of 90.60% and accuracy of an 93.33%. Dahane et al. [97] propose a novel EDGE–fog–IoT–cloud-based architecture that utilizes WSNs to support tilling activities in three steps: data collection from sensors (soil moisture, temperature, humidity, water level, etc.), data cleaning and storage, and predictive analysis through AI tools. Performance of Gated Recurrent Unit (GRU) and LSTMs on live data from three parameters is compared, with varying results. Jhuria et al. [9] propose a tool that utilizes ANNs to identify diseases in grapes and apples.Image processing is performed on an image dataset, and an accuracy of 90% is obtained basedon color and texture.

The study also provides a tool to determine the quality of fruit by weight. Bhange et al. [98] present a web-based tool for identification of fruit diseases trained on images of pomegranate fruit. The system processes an image uploaded by the user for parameters such as color and morphology, and classifies it as infected or non-infected usingSVMs. Accuracy of 82% was recorded using the 'morphology' parameter in the experiment. Guo et al. [10] propose a system for identification of plant diseases through the use of deep learning. The model identifies black rot, bacterial plaque and rust diseases by implementinga Region Proposal Network (RPN) for leaf localization, the Chan–Vese algorithm for leaf segmentation, and VGG-13 [99] architecture for disease identification.

This method providesan accuracy of 83.57%. In the study by Ferentinos [100], image classification through a VGG. CNN is performed on a database of 87,848 photographs of leaves of healthy and infected plants in a set of 58 distinct classes of [plant, disease] combinations, and a success rate of 99.53% is achieved. Similarly, smartphone-assisted crop disease diagnosis is performed by Mohanty et al. [101] on the PlantVillage dataset consisting of 54,306 images of plant leaves. The GoogleNet architecture performed the best out of all models tested, resulting in an accuracy of 99.35% on 14 crop species and 26 diseases. The prevention of fruit tree diseases can also significantly impact overall agricultural production. Li et al. [102] conducted a study comparing the performance of three ensemble learning classifiers and two deep learning classifiers. The stacking ensemble learning classifier provides the highest validation accuracy of 98.05% and test accuracy of 97.34% on a dataset of 10,000 images of pear black spot, pear rust, apple mosaic, and apple rust. Figure 4 displays a generalized example of plant disease identification through the use of CNNs. The network takes input in the form of segmented images and classifies them as 'Diseased' and 'Not Diseased'.

Due to the rapid increase in global meat consumption, technology (ies) such as precisionlivestock tilling [103] have become essential to ensure the quality of meat products and reduction of the environmental impact. AI tools can also prove beneficial in livestock management by monitoring cattle health and behavior. Xu et al. [104] propose a system forindividual identification of cattle through face detection, performed using the RetinaNet object detection algorithm. Fine-tuning was performed on seven different CNN models, and transfer learning was used for this study. RetinaNet incorporating the ResNet 50 provided the highest average accuracy of 99.8% and an average processing time of 0.0438 s. Gjergji et al. [105] evaluated the following neural networks for the regression task of cattle weight prediction: CNNs, Recurrent Neural Networks (RNN)/CNN networks, recurrent attention models, and recurrent attention models with CNNs. CNNs were shown to provide the best performance with MAE of 23.19 kg, significantly outperforming the top linear regression models, which reached an error of 38.46 kg. Jung et al. [106] present a deep learning-based system for classification of cattle vocals and real-time monitoring of livestock.

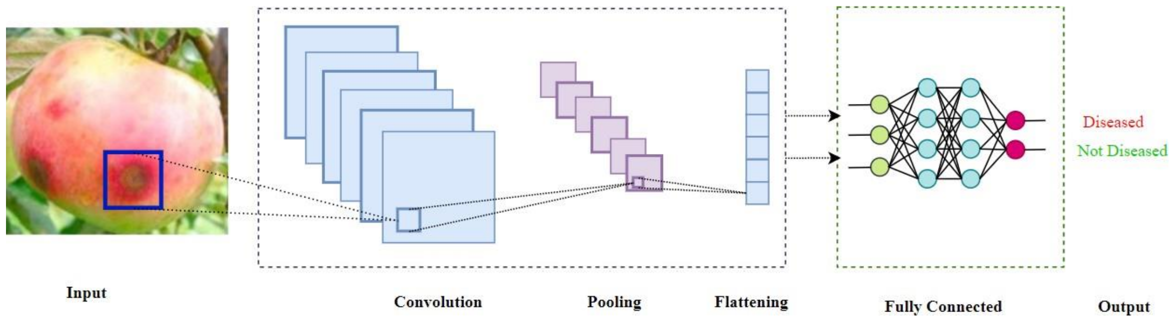

Figure 4. Disease identification through image processing.

The voice parameter of cattle can signal valuable information such as gender of cattle, distress, and disorders in the cattle [107]. The voice was converted to Mel- frequency cepstral coefficients (MFCCs) and given as input to a CNN for classification with an accuracy of 91.36%. The accuracy increased to 94.18% when short-time Fourier transform-based noise filtering was used to reduce background noise. In the context of smart tilling practices, deep learning has also been shown to be widely beneficial in the field of aquaculture. Fish production contributes to a great portion of the food source in any area. Zhang et al. [108] propose the use of DNNs for fish identification, species classification, analysis of fish behavior, feeding decisions, and water quality prediction.

The method provided an accuracy of 96% and recognition rate of 98% when trained on the Fish 4 knowledge dataset, which contains 8487 images of fish with different conditions. The study done by Rohani et al. [109] proposes a model consisting of multi-layer perceptron (MLP) and SVM for classification of rainbow trout as dead or alive. Both classifiers provided an average accuracy of 100% during the training phase and average of 99.45% during the testing phase. Zambrano et al. [110] propose the use of machine learning tools to forecast water quality variables such as dissolved oxygen, pH, and pond temperature. A comparison is performed between Random Forests (RF), ANNs, and multivariate linear regression, out of which RFs performed the best.

CNNs can also be used to perform object detection and pattern recognition on images collected by aerial vehicles to detect anomalies such as weed clusters, standing water, etc. Chiu et al. [111] introduce ‘Agriculture-Vision’, a large-scale dataset of aerial farmland images, designed for semantic segmentation of agricultural pattern recognition. The dataset consists of 94,986 high-quality aerial images consisting of RGB and near-infrared (NIR) channels. The study proposed a Feature Pyramid Network (FPN)-based model with a ResNet encoder to classify 9 field anomaly patterns. The mean intersection-over-union (mIoU) was 43.40% for the validation set and 43.66% for the test set. The first Agriculture-Vision Challenge [112] encouraged further development of novel algorithms for pattern recognition in agriculture. The challenge dataset consists of 21,061 aerial and multi-spectral farmland images, and six anomaly patterns were to be recognized in the task. The best- performing model, Residual DenseNet with Squeeze-and-Excitation (SE) block, introduced by Team DSCC, achieved a modified mIoU of 63.9%.

The study by Kussul et al. [113] performs classification of crops using MLPs, RFs, and CNNs. The dataset consisted of 19 multitemporal scenes acquired by Landsat-8 and Sentinel-1A RS satellites, and the highest classification accuracy of 94.6% was achieved by 2-D CNNs. Another crop vision dataset for species classification and detection is the CropDeep [114] dataset, which consists of 31,147 images and at least 1500 samples for each of the 30 classes. A baseline study showed the best performing model was ResNet50, with an accuracy of 99.81%. The study further suggests the YOLOv3 network with modification to achieve higher accuracy on the dataset. Anand et al. [115] present ‘AgriSegNet’, which is a multi-scale hierarchical attention network for semantic segmentation using UAV-acquired aerial images for IoT- assisted precision agriculture. The mIoU on the test set of the Agriculture-Vision dataset for the six anomaly classes are: Background: 78.10%; Double Plant: 46.40%; Planter Skip: 8.60%; Standing Water: 61.20%; Waterway: 44.90%; Weed Cluster: 50.20%.

Table 2. Summary of applications of CNNs in smart tilling.

Applications	Results
Plant disease detection through CNN [100]	99.53% success rate
Plant disease detection by CNN trained on 14 crop species and 26 diseases [101]	99.35% accuracy
CNN for identification of 6 diseases in tomato leaves [116]	AlexNet accuracy: 97.49%; VGG16 net accuracy: 97.23%
Plant disease detection by CNN trained on 13 crop species and 26 diseases [117]	MobileNet accuracy: 99.62%; iInceptionV3 accuracy: 99.74%
Cattle face detection through CNN: Object detection algorithm RetinaNet incorporating ResNet 50 [104]	Average precision score: 99.8%; Average processing time: 0.0438 s
Beef cattle body weight prediction through CNN [105]	Mean absolute error: 21.64 kg
Holstein Frisian cattle detection and individual identification through CNN [118]	99.3% accuracy
Species classification and detection on the CropDeep crop vision dataset done by CNNs [114]	Baseline study: ResNet50 average accuracy of 99.81%
Classification of crop types (maize, soybeans, etc.) done by MLPs, RFs and CNNs [113]	Highest accuracy of 94.6% by ensemble of 2-D CNNs
FPN-based model for semantic segmentation of agricultural land on the Agriculture-Vision dataset [111]	Mean intersection-over-union (mIoU) was 43.40% for the validation set and 43.66% for the test set.
Residual DenseNet with squeeze-and-excitation (SE) block on the Agriculture-Vision challenge dataset [112]	Modified mIoU of 63.9%

In this subsection, we emphasize several points regarding the opportunities providedby AI in the field of smart tilling. Image processing is of great importance to the agricul-tural sector. Images captured by UAVs, UGVs, satellites, and sensors need to be analyzed so that relevant insight can be extracted from them to assist in farm operations. Depending on the requirements, different types of cameras, such as visible spectrum, NIR, hyperspectral,or multispectral may be used. In conjunction with several ICTs, AI can efficiently perform functions such as crop monitoring, livestock monitoring, disease detection, pest detection,etc. Predictive modeling can assist farmers to prepare for extreme weather conditions and market fluctuations, thereby lowering their vulnerability. Current state-of-the-art modelshave provided promising results, implying that further re search in the area with more advanced AI tools can assist to bridge the gap in food production.

4. Initiatives Worldwide

This section includes the various re search initiatives that have been undertaken in smart tilling in the European Union [119] and across the world. The initiatives usually employ several of the ICTs and DTs discussed in Section 3. The European Union has funded many projects to permit for the integration of ICTs and DTs into the agricultural sector. Crop monitoring is one of the major functions performed in farms that utilize smart tilling tools. Table 4 provides an overview of the recent projects concerning the implementation of SF tools for crop monitoring that have been undertaken in the European Union. Table 5 lists the projects that perform other functions such as harvesting, water management, satellite imagery, and more. The corresponding technology (ies) for each project have also been listed along with their application. The Echord++ [120] project, which lasted from 1 October 2013 to 30 September 2018, involved various field operations such as monitoring, harvesting, and grafting for crops such as tomatoes, asparagus, and peppers.Cloud computing is utilized by many projects that require monitoring operations.

These include Vinbot [121] (crop monitoring and yield prediction in a vineyard), Ermes [122] (crop monitoring for rice), Fractals [123] (monitoring, disease detection, and fertilization of olivetrees), and more. The importance of UAVs and UGVs is apparent, as they have been utilized in several projects. Implementations of UGVs include Vinerobot [124] for a vineyard, Sweeper [125] for harvesting peppers, Flourish [126] for monitoring and spraying sugar beets and sunflowers, PANtHEOn [127] for monitoring hazelnuts and water management, and Romi [128] for crop monitoring and weed management. UAVs are utilized for crop monitoring of rice in Ermes [122], potatoes and vineyard in Mistrale [129], and more. Seamless communication between different technology (ies) has been executed through the use of WSNs, such as Water-Bee [130] and Figaro [131], for the purpose of water management.

Table 3. Summary of applications of Artificial Intelligence in Smart Tilling.

Applications	Results
K-means for clustering; SVM for classification of pomegranate diseases [98]	82% accuracy (morphology)
ANN for disease detection in grapes and apples [9]	90% accuracy (morphology)
RPN for localization of leaves; ChanVese algorithm for segmentation; transfer learning model for disease identification [10]	83.57% accuracy
ANN for paddy crop disease detection [96]	93.33% accuracy
Fruit disease identification by stacking ensemble learning classifier trained on apple and pear diseases [102]	Accuracy of 98.05% on validation dataset and 97.34% on test dataset
UAV-based plant/ weed classification with Random Forests [77]	Crop vs. weed classification accuracy of 96% and 90% recall
Soybean crop yields in Argentina using LSTMs; Transfer learning approach for Brazil soybean harvests [12]	RMSE of 0.54 for Argentina and 0.38 for Brazil (transfer learning from Brazil)
Deep neural network (DNN) for yield prediction of maize hybrids [13]	Yield prediction: training RMSE = 10.55, validation RMSE: 12.79 for DNN
Classification of fish in aquatic fish farms through DNN [108]	Accuracy = 96%, recognition rate = 98%
Random Forests for forecasting water quality variables such as dissolved oxygen, pond temperature, etc. [101]	RMSE for pond temperature = 0.5971, RMSE for dissolved oxygen = 1.616.
Recognition and classification of dead and alive rainbow trout eggs done by MLP and SVM [109]	Training accuracy = 100%; Average testing accuracy = 99.45%

Table 4. Smart Tilling projects in EU for crop monitoring.

Project Name	Technologies	Operations
Echord ++ [120]	Cloud computing; Image processing; Machine Learning; UAV; UGV	Crop monitoring; Harvesting; Weed management
Vinerobot [124]	Image processing; Machine Learning; UGV	Crop monitoring;Disease detection; Water management
Vinbot [121]	Cloud Computing; Image processing; UGV	Crop monitoring; Yield production
Flourish [126]	Image processing; UAV; UGV	Crop monitoring; Spraying
PANtHEOn [127]	Big data; UAV; UGV; WSN	Crop monitoring; Water management
Ermes [122]	Big data, Cloud computing; UAV; WSN	Crop monitoring
Fractals [123]	Cloud computing; WSN	Crop monitoring; Disease detection
Mistrale [129]	Image processing; UAV	Crop monitoring; Water management
Romi [128]	UAV; UGV	Crop monitoring; Weed management
Apollo [132]	Aerospace sensing	Crop monitoring
AgriCloud P2 [133]	Cloud computing; Edge computing; Information systems; Terrestrial sensing	Crop monitoring
Sensagri [134]	UGV; Terrestrial sensing; Aerospace sensing	Crop monitoring
IoF2020 [135]	Cloud computing; UAV; UGV; Big data; Aerospace and terrestrial sensing; Information systems	Crop monitoring; Livestock farming; Dairy monitoring
DataBio [136]	Machine learning; Big data; Aerospace and terrestrial	Crop monitoring; Forestry; Fishery

	sensing; Cloud computing	
Apmav [137]	Big data; Machine learning; UAV; Terrestrial sensing; Cloud computing	Crop monitoring
AfarCloud [138]	Big data; Terrestrial sensing; UGV	Crop monitoring; Livestock farming
BigDataGrapes [139]	Machine learning; Big data; UAV; Terrestrial sensing; Cloud computing; Information systems	Crop monitoring
Dragon [140]	Machine learning; Big data; UAV; UGV; Aerospace and terrestrial sensing; Information systems	Crop monitoring

There have been several re search projects on smart tilling taken up all over the world, in part inspired by the positive outcomes of the EU projects. Table 6 provides a summary of government projects and start-ups that focus on the development of innovative solutions for smart tilling. Some projects, such as the Villages of Excellence (VoE), have been launched in collaboration between two governments to ensure the sharing of technology (ies) and expertise and provide better outcomes for both. Smart irrigation plays an important role in ensuring crop sustainability in dry areas. Startups such as Madar Farms [141] and Responsive drip irrigation [142] aim to provide smart irrigation solutions to tackle water challenges and food security in the United Arab Emirates and the United States respectively. SunCulture [143] is a Kenyan AgriTech company that provides solar- powered irrigation systems for smallholder farms, and also provides the option of a drip irrigation system.

In Morocco, the government introduced the Green Generation 2020–2030 strategy [144], which focuses on the digitization of agriculture through initiatives such as the installation of solar pumps for irrigation. Food security and sustainability are of great concern worldwide. Startups such as AbyFarm [145] in Singapore aim to implement urban tilling by employing ICT and DT tools such as IoT and blockchain. Lack of resources in rural areas could be a hindering factor in crop yield. Ossian Agro Automation [146] is an Indian company working towards rural automation and the development of wireless automation systems. All year round production of crops can be achieved by vertical tilling, which is the practice of growing crops in many layers in a controlled environment. Ground vertical tilling [147] in Lebanon implements vertical tilling and aims to reduce water wastage by re-circulation. Figure 5 displays the various smart tilling projects taken up across the world, classified according to their primary function.

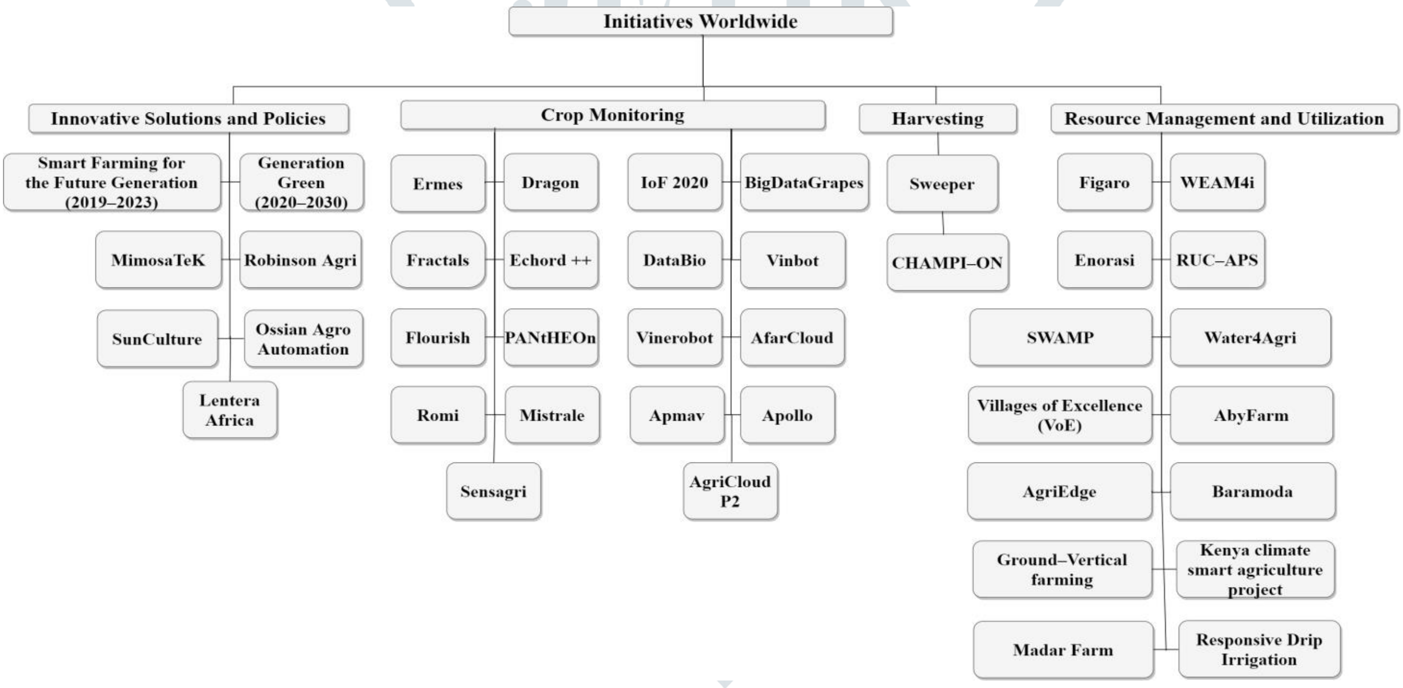

Figure 5. Smart Tilling initiatives worldwide

In several developing countries, there is a lack of government-funded projects. The initiative is rather taken up by individual startups, with the goal to provide assistance to farmers, conduct further re search, and educate farmers and learners about the potential of agricultural technology (ies). There is an increased interest amongst consumers, who want to ensure that the end product they receive is unadulterated. Public opinion in Europe skews in favor of healthy products grown with minimum pesticides. Consideration of the socio–economic impact of smart tilling projects is also necessary. Certain participating farms have reported average cost savings of over €5000 and reduction of climate impact by10% [148]. Thus, these initiatives have been greatly beneficial to tilling operations by de- creasing costs, reducing greenhouse emissions, and improving soil conditions. The projects contributed significantly to their objectives of reducing resource wastage, environmental impact, and energy consumption, and demonstrated measures to mitigate issues resultingfrom climate change and the shortage of skilled labor.

5. Sentiment Analysis

In order to ensure successful integration of new tools and technology (ies) available for smart tilling, it is necessary to understand how knowledgeable the general public is about the topics and how the innovations are perceived. Public sentiment can be a strong determinant of whether or not a project is approved for implementation in an area [166]. It can also be indicative of the various socio–economic, behavioral, and cultural issues that arise by the advancement and implementation of such technology (ies) [28,167]. In light ofthis, we performed sentiment analysis on the comments of YouTube videos pertaining tosmart tilling technology (ies). This section provides details about the dataset, experimentalmethodology, and the results and analysis of the experiment.

5.1. Dataset

The dataset was constructed by scraping YouTube comments left by users on 16 YouTubevideos that were relevant to our study [168–172]. The videos were selected by searching the relevant keywords, such as 'smart tilling IoT', and then filtering the ones with most views and comments. Table 7 provides a list of the video titles, the channels, upload date,and the total number of likes and views on each video. For this study, only commentsin English were considered. A total of 7311 comments were included in the dataset from videos about smart tilling.

5.2. Experiment

Two approaches were used for performing sentiment analysis. In the first approach, twoannotators assigned one of the following six labels to the comments: 'Praising', 'Queries', 'Suggestions', 'Undefined', 'Hybrid', and 'Opinion'. Cohen's kappa coefficient, which is a measure of inter-rater agreement, was calculated on the ratings of the two annotators. The value of the kappa statistic ranges from 0 to 1, with 0 implying only a chance agreement and 1implying perfect agreement between the two annotators.

The formula to calculate Cohen's kappa for two raters is:

$$\kappa = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e} \quad (1)$$

where: p_o = the relative observed agreement among raters, and p_e = the hypothetical probability of chance agreement.

A brief description of these labels is given in Table 8, along with the total number ofcomments for each label, and an example of the label from the dataset. Table 9 gives the total counts of each of the six labels that were assigned to the comments collected from the videos.

Table 5. Smart Tilling projects in EU.

Project Name	Technology (ies)	Operations
Sweeper [125]	Image orocessing; UGV	Harvesting
Figaro [131]	WSN	Water management
Enorasis [149]	WSN	Water management
WEAM4i [150]	Cloud computing; WSN	Water management
CHAMPI-ON [151]	Image processing; Machine learning	Harvesting
Auditor [152]	Aerospace sensing	Satellite imagery
RUC-APS [153]	Cloud computing; Edge computing; Information AfriCul	Management; Optimization
AfriCultuReS [154]	Big data; Aerospace and terrestrial sensing; Cloud computing; Information systems	Food Security
SWAMP [155]	Big data; UAV; Terrestrial sensing; Cloud computing; Information systems	Water use
Water 4Agri [156]	Aerospace sensing	Water use

Table 6. Smart Tilling initiatives worldwide.

Project/ Company	Country/ Countries	Objectives
Villages of Excellence (VoE) (2021-23) [157]	AbyFarm [145]	Improve the productivity and quality of horticulture; Increase income of farmers
Nosho Navi 1000 (2014-16) [158]	Japan	Large-scale smart rice tilling
Baramoda [161]	Egypt	IoT, blockchain and machine learning for urbantilling to ensure sufficiency of crops
Smart Tilling for the Future Generation (2019-23) [159]	Vietnam and Uzbekistan	Development of policies, enhancement of skills and knowledge. Support farmers through post-harvest handling and markets
AgriEdge [160]	Morocco	Precision agriculture platform for practices such as efficient use of water and fertilizer, monitoringweather data, and satellite imaging.
Generation Green (2020-30) [144]	Morocco	Introduction of new technology (ies) for sustainable agriculture; Installation of over 100,000 solarpumps for irrigation
Agricult	Lebanon	Sustainable agriculture; Maximize the efficiencyof agri-waste management
Ground – Vertical tilling [147]	Lebanon	Improve efficiency of agricultural yield; Reduce water consumption and costs.
Robinson Agri [162]	Lebanon	Greenhouse technology (ies)
Kenya Climate Smart Agriculture Project (KCSAP) [163]	Kenya	Improve productivity in case of climate changerisks and provide response in emergencies

Mimosa Tek [164]	Vietnam	IoT platforms for precision tilling solutions
Ossian Agro Automation [146]	Far	Wireless automation systems (Nano Ganesh) forirrigation in rural areas
SunCulture [143]	Kenya	Solar-powered irrigation systems (RainMaker2)
Madar Farm [141]	UAE	Ensure food and water security
Responsive Drip Irrigation [142]	USA	Smart irrigation
Lentera Africa [165]	Kenya	Technology (ies) enabled farmer advisory services; the world

The second approach was to apply transfer learning to perform surface level sentiment analysis using the pre-trained Pattern library for Python. Pattern library can be used to perform various natural language processing tasks such as parsing, N-gram generation, and more. Polarity of a given text ranges from 1 to 1, with 1 representing a highly positive sentiment and 1 representing a highly negative sentiment. The subjectivity ranges from0 (Objective) to 1 (Subjective).

It provides a measure of factual information or personal opinion in the comments, with 1 being subjective and 0 being objective. For example, for the following comment in our dataset: 'Fantastic. We need a lot of that here in Australia; suffering from drought; really bad water management by those in authority etc.' , the polarity was calculated as 0.1499 and subjectivity was 0.7833. The negative value of polarity indicates that the sentiment expressed by the comment was negative, whereas thevalue of subjectivity is closer to 1 suggesting that the comment was mostly subjective.

Table 7. Videos selected for sentiment analysis

S.No.	Title	Channel	Likes as of April/2022	Upload Date	Views
01	How japan is reshaping it's agroculture by harnessing samrt-farming technology	science inside	1100	08/03/21	35,000
02	Europe has the best regenerative farmers in the world	richard perkin	543	08/10/20	16,000
03	The futuristic farms that will feed the world	freethink	22,000	19/08/19	805,000
04	Vertical farms could take over the world	freethink	26,000	22/05/21	753,000
05	India's largest precision farm	discover agricultur	2500	12/03/21	70,000
06	Solar panels plus farming? agrivoltaics explained	undecided with matt ferell	59,000	05/10/21	1.9 million
07	7 Israeli agriculture technologies	israel	35,000	21/01/19	2.0 million
08	The cnh industrial autonomous tractor concept	cnh industrial	17,000	30/08/16	2.7 million
09	IoT smart plant monitoring system	viral science – the home of creativity	6800	20/12/20	341,000
10	Singapore's bold plan to build the farms of the future	tomorrow's build	30,000	13/07/21	1.8 million
11	Smart vertical farms in sharjah	episode up	1200	17/09/20	59,000
12	Drones, robots and super sperm – the future of farming	dw documentary	6700	07/02/19	919,000
13	Simply fresh – india's largest state of the art precision farm	simply fresh	7100	10/10/20	314,000
14	RIPPA the farm robbot exterminates pests and weeds	abc science	8800	14/05/18	813,000
15	Top 10 agritech startup's empowering indian farmers	backstage with millionaires	11,000	09/06/20	325,000
16	This farm of the future uses no soil and 95% less water	stories	152,000	05/07/16	152,000

Table 8: Label Description

S.No.	Label	Description	Example
01	Praising	Simple positive response	This is amazing! Everyone is a winner when we chose sustainability!
02	Suggestion	Any concrete suggestion relevant to the topic	Technology is really spectacular, now just assess its viability.
03	Opinion	Positive, negative, or combined sentiment	Technology is taking over farming, I like having to do it the way they do it now
04	Undefined	Undetermined or isn't relevant	That would be like playing tilling simulator in real life!
05	Hybrid	More than one of the categories	Best part of far,big is driving a tractor, get a robot to shovel manure, do chores like that would be sweet.
06	Queries	Any concrete queries relevant to the topic	I wonder how much this thing costs

5.3. Results and Analysis

In this section, we detail the results of our experiment and analyze our findings. Evaluation has been conducted separately for the two approaches through user-based analysis and transfer-learning-based analysis. Table 10 records the number of comments under a video and the results obtained from sentiment analysis. The value of mean polarity, mean subjectivity, and Cohen's kappa coefficient is listed for each corresponding video serial number.

5.4. User-Based Analysis

In user-based analysis, the mean Cohen's kappa was calculated to be 0.9617, which shows high inter-rater reliability. Figure 6 displays the Cohen's kappa coefficient for eachvideo with respect to the mean value. The value is highest at 1 for videos no. 5, 9, and 12, indicating perfect agreement between the labels assigned by both annotators. The value is lowest at 0.8141 for video no. 2 titled 'Europe has the best regenerative farmers in the world', implying a slight disagreement between the assigned labels. The high value of kappa coefficient implies that the categories assigned by the annotators are correct.

Figure 7 plots the correlation matrix between the frequency of the six labels. We can see the highest degree of correlation is 0.96 between the following labels: 'Opinion' and 'Suggestion', and 'Queries' and 'Hybrid', indicating that the frequency of one increases with the other. The lowest degree of correlation is 0.81 between 'Hybrid' and 'Undefined',suggesting that all labels show a relatively positive correlation amongst each other.

Table 9. Number of comments of each label type.

Video Serial No.	Praising	Suggestion	Opinion	Undefined	Hybrid	Queries
01	14	5	3	5	0	2
02	8	2	10	2	2	4
03	33	7	83	14	20	21
04	98	33	504	176	81	149
05	8	0	5	3	0	4
06	31	15	70	25	47	11
07	61	1	17	50	12	16
08	31	9	351	233	17	54
09	39	4	5	29	15	110
10	129	39	399	225	29	57
11	26	2	4	2	4	3
12	36	4	113	36	9	9
13	94	0	24	4	24	32
14	23	14	155	126	8	33
15	54	14	45	23	13	15
16	273	85	1455	438	218	466

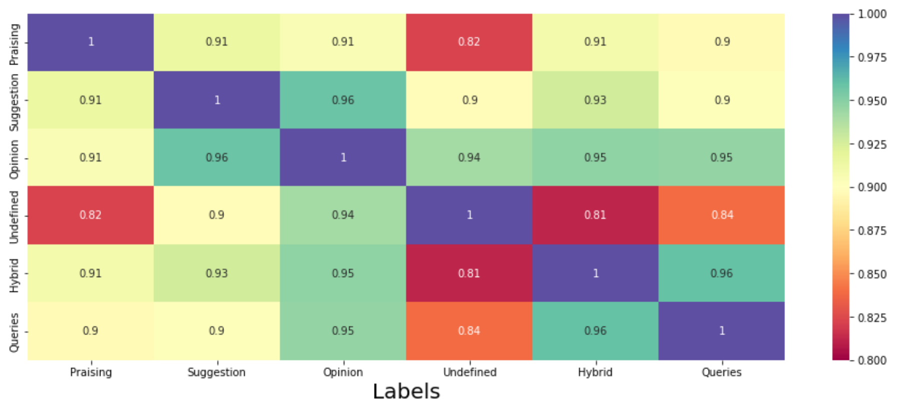

Figure 7. Correlation heatmap between assigned labels.

A word cloud is a data visualization technique used for representing text data wherethe frequency or importance of each word is indicated by its size. It can assist us highlight and analyze significant textual data points. Pre-processing of the comments was performed to remove stop words and punctuation from the text. Figure 8 displays the word clouds for the comments collected from videos of serial number 1–8. We can see that on the word cloud in Figure 8a, which is for the video titled ‘How Japan Is Reshaping Its Agriculture ByHarnessing Smart- Tilling Technology (ies)’, ‘Japan’ is one of the most frequent and important words in the text. Similarly, for Figure 8g for video no. 7 on the bottom left titled ‘7 Israeli Agriculture Technology (ies)’, the most significant word is ‘Israel’. Figure 9 displays the wordclouds for the comments collected from videos of serial number 9–16. The word 9b on thetop left for the video titled ‘Singapore’s Bold Plan to Build the Farms of the Future’ has ‘Singapore’ as the most prominent word.

Table 10. Results of Sentiment Analysis

Video Serial No.	No. of Comments	Mean Polarity	Mean Subjectivity	Kappa Coeff.
01	29	0.2143	0.3124	0.9061
02	28	0.2546	0.4956	0.8141
03	178	0.2262	0.4809	0.9609
04	1041	0.1420	0.4197	0.9890
05	20	0.3104	0.4197	1.0
06	157	0.3404	0.4710	0.9467
07	695	0.0919	0.3838	0.9526
08	202	0.1743	0.2915	1.0
09	878	0.1417	0.4087	0.9698
10	41	0.3849	0.5369	0.9571
11	207	0.1172	0.4116	1.0
12	178	0.4360	0.5480	0.9827
13	359	0.1186	0.3734	0.9958
14	164	0.2736	0.4614	0.9921
15	2935	0.1942	0.4546	0.9995
	Average Score	0.2092	0.4352	0.9617

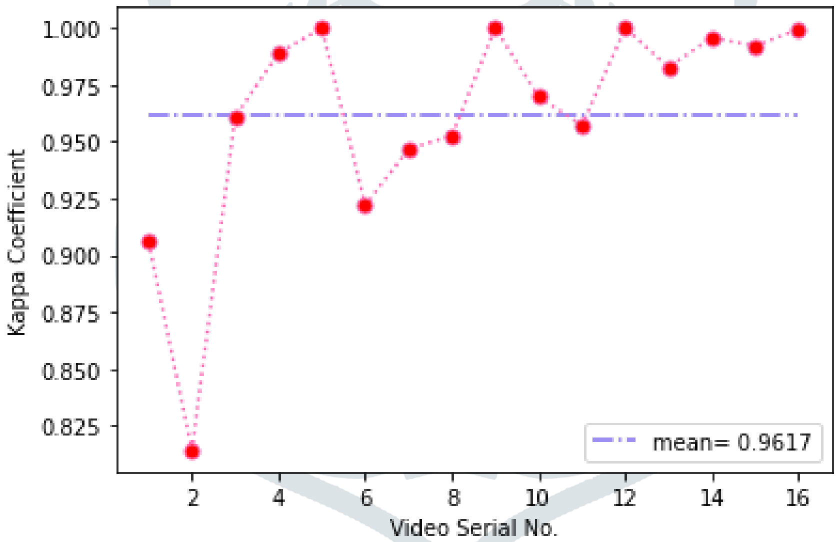

Figure 6. Cohen’s Kappa Coefficient plotted against mean value of 0.9617.

This indicates that several comments for these videos included some text about the country in which the technology (ies) was implemented. For videos demonstrating a particular technology (ies), such as No. 7: ‘Solar Panels Plus Tilling? Agrivoltaics Explained’; No. 8: ‘The CNH Industrial Autonomous Tractor Concept (Full Version)’; and No. 14: ‘RIPPA The Farm Robot Exterminates Pests And Weeds’, the name of the technology (ies) (solar, tractor, robot, respectively) is of great prominence. Table 11 provides a list of the top five most-relevant words in the comments dataset for each video, along with their respective frequencies.

Transfer-Learning-Based Analysis

The results of sentiment analysis using the Pattern library are discussed in this sub- section. Mean polarity and mean subjectivity are plotted opposite each other in Figure 10. The overall polarity for all 7311 comments is 0.2092, suggesting that the overall sentimentis slightly positive. The overall subjectivity of all comments is 0.4352, implying that the comments were close to being neutral. Subjective statements generally contain personal opinion, emotion, or judgment, whereas objective comments are factual information. Po- larity determines the degree of positive or negative sentiment in the text. The highest mean subjectivity score was 0.5480 for video no. 13 titled ‘Simply Fresh—India’s Largest State Of The Art Precision Farm’, followed by 0.5369 for video no. 11 titled ‘Smart Vertical Farms in Sharjah’. This shows that the comments were of a more opinionated nature, rather than being factual. The lowest mean subjectivity score was 0.2915 for video no. 9 titled ‘IOT Smart Plant Monitoring System’, indicating that mostly facts were discussed in the comments for this video. The score suggesting higher objectivity could be because the video is discussing technical details about an IoT platform rather than explaining widespread innovative concepts such as precision farms and vertical farms. The comments collected from video no. 8 titled ‘The CNH Industrial Autonomous Tractor Concept (Full Version)’ resulted in the lowest mean polarity of 0.0919, indicating that the user sentiment was generally neutral. The highest mean polarity of 0.4460 was achieved for video no. 13 titled ‘‘Simply Fresh—India’s Largest State Of The Art Precision Farm’, showing that user attitude was generally positive towards the state-of-the-art precision farm highlighted in the video.

Figure 8. Word clouds for videos serial no. 1–8 corresponding (**a**–**h**) respectively

Figure 9. Word clouds for videos no. 9–16 corresponding (**a**–**h**) respectively.

In the investigation of user sentiment towards smart tilling and precision agriculture, the main objective was to analyze user opinion, which is the voice of masses. During compilation of the dataset, it was observed that videos providing more in-depth and case-study-based information about smart tilling tools did not receive many views andcomments. This could be because the general public is not well-informed about novel technology (ies) in the tilling sector, as asserted in Section 6. The majority of the comments were collected from videos about broader topics. The Cohen's kappa coefficient indicated that the labels assigned by the two annotators were mostly in agreement and valid. The mean values of polarity and subjectivity in the comments was calculated through the Pattern library, and the results suggest that there is a varying degree of subjectivity amongst the comments. The polarity suggests that user opinion was mostly positive in the comments analyzed. Thus, it can be safely inferred that training and education programs can increasethe visibility of innovations in smart tilling, permiting the general population to form a well-informed opinion on the risks and benefits. Positive user sentiment can then serve asa catalyst towards faster adoption of such tools.

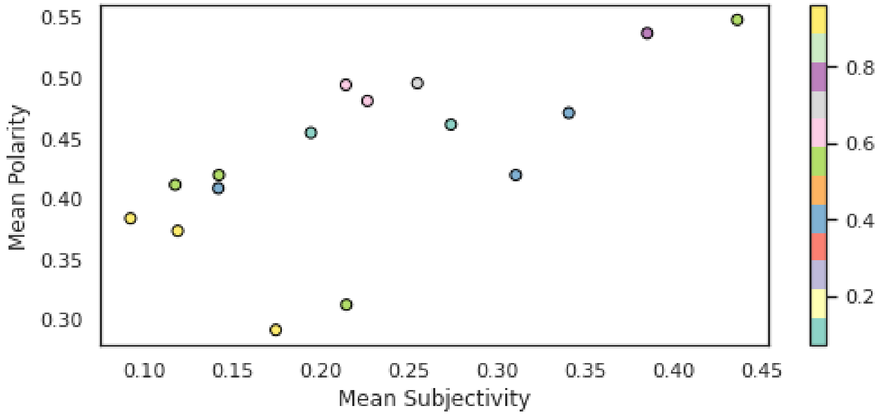

Figure 10. Mean polarity vs. mean subjectivity.

Table 11. List of five most frequent words for each video with respective frequencies.

Video Serial No.	Most Common	2nd	3rd	4th	5th
01	technology (ies) (6)	japanese (5)	japan (5)	video (4)	good (4)
02	richard (5)	regenerative (4)	love (4)	tilling (3)	start (3)
03	food (66)	tilling (29)	sustainable (21)	energy (21)	water (20)
04	tilling (183)	food (157)	vertical (151)	grow (109)	people (97)
05	hands (2)	environment (2)	farmer (2)	corporate (2)	awesome (2)
06	solar (129)	panels (101)	energy (56)	water (51)	land (41)
07	israel (42)	love (35)	india (21)	agriculture (13)	technology (13)
08	tractor (109)	tilling (104)	farm (61)	farmer (57)	work (56)
09	project (39)	code (26)	software (24)	sir (24)	error (22)
10	singapore (201)	food (145)	tilling (88)	people (83)	firms (70)
11	great (9)	video (8)	good (7)	farm (5)	food (5)
12	tilling (30)	future (24)	people (22)	cow (18)	nature (18)
13	great (36)	tilling (26)	work (24)	sir (24)	farm (22)
14	robot (42)	robots (30)	people (27)	farm (22)	good (19)
15	video (36)	great (25)	farmers (24)	india (24)	good (19)
16	plants (430)	food (429)	tilling (355)	water (332)	soil (319)

6. Challenges

There has been a significant increase in the number of smart tilling initiatives beingtaken up around the world, with promising results. However, with the advent of new, innovative technology (ies) there are always some unseen risks and associated challenges. The agricultural sector has greatly impacted the environment by taking up about 40% of the world's available land [173] and consuming approximately 70% of the water [174]. Climate change and the growing population further exacerbate food and water scarcity, making sustainable food production a challenging task. Thus, it is critical that current agricultural practices need to evolve to ensure the efficient use of land and water resources.To elaborate further on Re search Question 2, we discuss the various challenges that hamper the adoption of smart tilling in the following bullet points:

Training and awareness: Lack of technical expertise by the farmers implementing new technology (ies) is a major setback to smart tilling. Das et al. [28] conducted a study to understand the views of Irish farmers towards adoption of cloud computingand smart tilling technology (ies). Surveys and interviews conducted with 32 farmers revealed that the rate of adoption was higher among younger farmers and lower amongst older farmers, who were hesitant to use new technology (ies) and preferred traditional tilling. The digital divide has to be reduced by providing guidance and training to the farmers [175]. Lack of knowledge about the technology (ies) results in greater skepticism towards its adoption amongst farmers, who may not realize the value of the tool or consider it an unsuitable fit for their farm. In this current study, we formed a dataset of YouTube comments related to smart tilling operations and performed surface level sentiment analysis of them. During the data collection process, it was observed that very few comments were left under videos that provided a technical and detailed framework for a smart tilling project. Comments were mostly collected from videos explaining broader topics, such as 'Vertical Tilling'. This indicates that there is a general lack of awareness about these technology (ies) and their applicability to tilling.

Technical considerations: Fixed and moving sensing technology (ies) require further improvements to be able to withstand extreme weather conditions in order to remain fully functional [176,177]. Edge node devices may be battery dependent and run out of power during operation [178,179]. Data is collected from various sensors and can be analyzed through IoT platforms. There is a requirement for data storage, as there is a huge amount of data being generated from IoT devices. IoT has improved connectivity of all operations by leaps and bounds, but it does come with the added concern of data privacy and security [180]. It also exposes the smart tilling environment to cybersecurity threats, which could result in significant loses [181]. Data encrypting in the Industrial Internet of Things (IIoT) also presents a significant challenge for farmers [182].

Costs: The costs associated with sensors needs to reduced so that they can be imple-mented in small-scale farms as well. The solution needs to be designed specifically for the project in question, and also needs regular updates and management. Farmers may hesitate in implementing such technology (ies) as they could create issues and cause further losses instead of providing benefits. Re search and development costs for the implementation of such tools are also steep. There is also a significant amount of costassociated with data transmission within a smart farm [183]. Market uncertainty adds substantial risk to ensuring a sustainable income for farmers, as profit margins are getting increasingly smaller. Farmers in small-scale agricultural fields are hesitant to use upgraded technology (ies) because of the high initial costs, perceived risks, and complexity of the system.

Government support: The laws and regulations in the area where smart tilling is being considered for implementation play a huge role in its eventual success or failure. The local governments are responsible for taking initiatives and providing funding and support training programs for the adoption of such tools [184]. Several successful initiatives taken up in the European Union [119] and across the world [144] have highlighted the importance of the effort taken up by regulatory bodies.

Ethical considerations: Human safety is also a concern in the operation of unmanned vehicles [185]. Collisions with the ground or other objects may also cause damage to the vehicle. It is also essential that the UAVs be flown in unrestricted areas. Currently, it is not clear where the accountability for the actions taken by autonomous vehicles lies. Data need to be uploaded to cloud systems in a secure manner, keeping regulations in mind. It is necessary for smart tilling operations to be transparent so that they are more trusted and accepted. The ownership of agricultural data is a huge liability that needs to be kept in mind. There are also legal and ethical considerations with the potential mishandling and misuse of these data [186]. Animal welfare is also a concern while making use of autonomous robots to perform functions such asmilking [187].

Regional considerations: Lack of proper infrastructure, such as roads, can be a major hurdle towards the advancement of smart farms, as the necessary resources and technology (ies) will not be successfully transported. There is limited availability of internet in rural areas, where smart tilling could be of greater significance. Standard protocols and frameworks for wireless communication cannot be defined, as the requirements rely heavily on the specific use case [188]. Further, communication protocols implemented within the smart farm may only provide coverage over smallareas [189].

7. Discussion

This review study was conducted to assess the challenges and opportunities in smart tilling by exploring current state-of-the-art ICTs and DTs, analyzing global projects, and understanding the perception of the general public towards such innovative practices. The two hypothesis stated at the beginning of the study have been supported by the findings of the re search questions, which have been answered as follows:

Hypothesis 3. *ICTs and DTs can be used in the agricultural sector to make significant improve-ments in several tilling applications.*

The following re search question was crafted to accept or reject the hypothesis:
What are the state-of-the-art ICTs and DTs currently used in smart tilling?
Over the last decade, several smart tilling projects have been launched across the world that were powered by technology (ies) such as IoT, wireless sensor networks, unmanned vehicles, etc., as detailed in Section 3. The potential use cases for each technology (ies) are discussed in Section 4, although several projects utilize more than one. Several re search projects in the European Union [18] and worldwide have also been discussed. The development of precise sensors enables the capture of data with higher accuracy, thus enabling better quality analysis and decision making [14]. Decision support systems can guide the farmer with operational decisions about choice of crop, frequency of fertilizer use, better utilization of resources, and more [69]. Autonomous vehicles take care of labor-intensive tasks, thus freeing up farmers for other important tasks [77]. Communication between various IoT devices through a WSN can permit for effective monitoring of the farm throughout the day, making it easier for the farmer to make operational decisions [36]. Blockchain technology (ies) can ensure that the supply and raw materials purchased are of good quality and there is no adulteration taking place [48]. DTs such as artificial intelligence also have an array of potential applications in smart tilling, building upon the availability of massive amounts of heterogeneous data from sensors [20]. We have discussed the use of machine learning and deep learning for disease identification in crops, fruits, and cattle in Section 3.7. AI has also shown great potential in optimizing resource utilization by automating timely irrigation, performing preemptive actions if a certain parameter crosses a threshold, and predictive analysis of weather and crop conditions [188]. AI can also be used to identify optimal conditions for growing crops and preventing crop wastage. Image processing is of great relevance in smart tilling, as there have been several studies that implement CNNs [98]. Image processing can be used for livestock management, guiding the decision-making processes of harvesting robots and pest and weed elimination drones. It can also enable precision tilling by collecting data from sensors and deploying resources accordingly [9].

Hypothesis 4. *There are certain significant challenges to the widespread adoption of smart tillingtools, such as lack of awareness about the topic amongst the general population.*

The following re search questions are explored in this context:
What are the challenges associated with the widespread adoption of smart tilling tools?
Despite the increasing number of smart tilling projects being launched all overthe world, there still exist many factors that hinder the widespread implementa- tion of such tools [6,188]. As we have discussed in Section 6, the limitations can be broadly categorized as lack of training and awareness, technical considerations, costs, government support, ethical considerations, and regional considerations. Technical difficulties arise due to the inability of current systems to withstand extreme weather and atmospheric

conditions, being too bulky and costly to implement, and not provid- ing up-to-the-mark accurate data [176]. Another challenge is the proper infrastructure required for storing and processing large amounts of data collected from sensors [181]. The privacy and security of this data is of great importance. Regional limitations could be the lack of infrastructure and connectivity. Smaller farms in rural areas could benefit greatly from the use of smart tilling tools. However, most smart tilling practices require the use of internet connectivity, which is sparse in rural areas. Other factors that hamper the development of smart tilling may include lack of techni- cal expertise by farmers, insufficient incentives provided by the government for the implementation of such practices, and skepticism of farmers towards the benefits of smart tilling [28]. General awareness amongst farmers is generally low and can be increased through training programs. Although smart tilling tools are generally black-box techniques, farmers making use of them still need to understand their operations so that they can consider the process reliable. Cost considerations could also make farmers skeptical towards installing new tools, as the upfront expenditure may be too much [183].

What are the current opinions and expectations of the digital user with regard to smart tilling?
In order to better understand user perception of smart tilling technology (ies) [166], we performed sentiment analysis on relevant English comments collected from YouTube [168], as detailed in Section 5. The comments were collected from 16 different videos that detailed innovative tilling solutions. Then, two different approaches to observe user sentiment were utilized. In the first approach, comments were man- ually labeled by two annotators into one of the following six categories: Praising, Queries, Suggestions, Undefined, Hybrid and Opinion. Cohen's Kappa coefficient, which is the measure of inter-rater reliability, was calculated as 0.9617. This shows a high rate of agreement between the labels assigned by both annotators. The labels also show high positive correlation with each other, as depicted in Figure 10. Word clouds created for each video in Figures 8 and 9 highlight significant words, such as 'technology (ies)', 'tilling', 'solar', etc. In the second approach, polarity and subjectivity were calculated for each comment using Pattern library for Python. The polarity score ranges from 1 (negative) to 1 (positive) and indicates whether the sentiment is positive or negative. The overall polarity was calculated as 0.2092, indicating a slightly positive sentiment. The subjectivity score ranges from 0 (objective) to 1 (sub- jective) and indicates the degree of factual information or opinion in the statement. The overall subjectivity was calculated as 0.4352, suggesting that the comments were slightly objective. This implies that the comments discussed were fact-based rather than opinionated. However, only a rudimentary study was performed to determine user sentiment, and better results can be achieved using state-of-the-art models for sentiment analysis. In the brief overview of user sentiment conducted in the study, we noticed lack of user comments on informative and technical videos about smart tilling platforms, indicating that a knowledge gap and a digital divide exists for such technology (ies) [175], which can be detrimental to their widespread adoption. The general attitude of users towards smart tilling technology (ies) is superficial, as the public is not well-informed about these topics.

8. Conclusions

Ensuring a sustainable food supply for the ever-increasing global population has become a necessity due to the unprecedented changes in the environment. The agricultural sector must update its practices in light of the worsening strain on land and water resources, and data-driven approaches provide such an opportunity to ensure sustainability. This study provided an overview of ICTs and DTs in automating and streamlining tilling operations, and demonstrated how smart tilling can improve crop yields by monitoring, disease prevention, automation of sowing and harvesting, etc. Examples of primary technological tools available for smart tilling are IoT, unmanned vehicles, remote sensing, predictive analysis through big data, and so on. This shift towards data-driven approaches enables tilling facilities to utilize available resources for maximum yield. The study also presents various challenges that are associated with large-scale implementation of smart tilling practices, such as poor connectivity in rural areas, insufficient funds and skilled labor, skepticism from farmers, concerns with data privacy, and more. To analyze the attitude of the public towards implementation of smart tilling, we performed sentiment analysis on comments from YouTube channels related to smart tilling. Preliminary findings in both user-based and transfer-learning based opinion mining suggest that a better understanding of smart tilling tools would assist the public in forming an informed opinion. Further advances are required to improve precision, cost, and efficiency of robots, sensors, and unmanned vehicles before they are readily adopted. Keeping the barriers to adoption for smart tilling techniques in mind, the future scope of re search would be to develop techniques that provide greater adaptability, ensure food sustainability, reduce cost, and counter the harmful affects of climate change on agriculture. Greater connectivity in rural areas could accelerate the integration of ICTs in smallholder farms, permiting them to prepare for unprecedented changes in tilling conditions. Further re search and investigation of the possible uses of DTs and ICTs is necessary to understand the challenges and opportunities in smart tilling. A detailed sentiment analysis using advanced language models and inclusion of non-English comments can also provide greater insight into the expectations and opinions of digital users towards innovative tilling solutions. Multidisciplinary re search also needs to be conducted to elucidate other socio–economic, environmental, and technical factors that impede development and adoption of such innovations.

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