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Smart Dairy Farming Focusing on Cattle Milk Yield Prediction Using Machine Learning

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智慧酪農業—應用機器學習於牛乳產量預測

Smart Dairy Farming Focusing on Cattle Milk Yield Prediction Using Machine Learning

本報告係陳冠伶君（R10459003）在國立臺灣大學國際三校農業生技與健康醫療碩士學位學程、所完成之碩士學位主題性統整報告，於民國 112 年 6 月 26 日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

牛奶和乳製品在人類社會中扮演著重要的角色。然而，酪農業目前正面臨許多挑戰，例如需求增加、勞動力短缺和氣候變遷等。為了應對這些問題，牛奶生產系統有待改進。智慧酪農業將物聯網（IoT）、大數據分析、人工智慧（AI）等技術應用於牧場，為這些挑戰提供創新的解決方案。智慧酪農業包含四個要素：環境控制、個體動物資訊、自動飼養系統和牧場管理，涉及熱緊迫控制、個體動物辨識、動物健康監測、自動榨乳系統、精準餵飼和精準育種等主題。乳量預測是智慧酪農業中的關鍵技術，它可以幫助農民預測農場收入、監測動物健康並優化育種選擇。本研究的目標是建立機器學習模型來預測乳量，並評估乳量與其他特徵之間的關係。本研究的資料來源為台灣乳牛群性能改良（DHI）計畫的資料庫，包含了 33,185 筆自 2013 年至 2018 年、共 1,818 頭荷蘭牛的榨乳記錄。經過數據清理和分析後，本研究使用不同的機器學習演算法來建立預測模型，包括支持向量機（SVM）、隨機森林（random forest）和 XGBoost。研究結果顯示，最終的 XGBoost 模型在三種演算法中表現最佳，其對未來乳量預測的準確率達到 76.33%。此外，本研究還發現影響乳量的重要因素為過去平均產量、泌乳天數、與前一胎間隔和月齡。這些結果對乳量預測的發展具有重要意義。

關鍵字：智慧酪農業、精準畜禽飼養管理、動物健康監測、乳量預測、機器學習

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Abstract

Milk and dairy products play a significant role in human society. However, milk production is currently facing several challenges, such as an increasing demand, labor shortages, and climate changes. To address these issues, improved milk production systems are required. Smart dairy farming incorporates the Internet of Things (IoT), big data analytics, artificial intelligence (AI), and other technologies in dairy farms, offering innovative solutions to these challenges. Smart dairy farming is made up of four elements: environmental control, single animal information, automatic rearing systems, and management, involving topics like heat stress control, individual animal identification, animal health monitoring, automatic milking systems, precision feeding, and precision breeding. One crucial aspect of smart dairy farming is milk yield prediction, which allows farmers to get a projection of farm income, monitor animal health, and optimize breeding selection. The objectives of this study were to develop machine learning models for milk yield prediction and to assess the relationship between milk yield and other features. The data used in this study were obtained from Dairy Herd Improvement (DHI) database in Taiwan, which included 33,185 milking records from 2013 to 2018 involving 1,818 Holstein cattle. After data cleaning and analysis, prediction models were built using various machine learning algorithms, including support vector machine (SVM), random forest, and extreme gradient boosting machine (XGBoost). The findings of this study demonstrated that the final XGBoost model exhibited the highest performance among the three algorithms, attaining an impressive 76.33% accuracy in predicting future milk yield. Moreover, it was revealed that specific factors, including average yield, days of lactation, calving interval, and age in months, significantly influenced milk yield. These insights serve as valuable contributions to the advancement of milk yield prediction.

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Keywords: smart dairy farming, precision livestock farming, animal health monitoring, milk yield prediction, machine learning

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Introduction

Milk and dairy products are crucial to humans due to their economic, social, and health contribution. In 2020, the global dairy market size was USD 708.7 billion (Fortune Business Insights, 2022). The total milk production was 912.6 million tons, with global trade in dairy products reaching 86.6 million tons. On a per capita basis, the average consumption was 116.4 kg/year in milk equivalents (Food and Agriculture Organization of the United Nations [FAO], 2022). The vast dairy industry was estimated to provide the livelihood of 1 billion people along the dairy value chain worldwide (International Dairy Federation [IDF], 2019). Furthermore, milk and dairy products are recognized as essential components of a healthy and balanced diet. Milk, being the primary source of nutrition for young mammals, contains all the necessary nutrients for growth and development (Pereira, 2014). One of the most well-known health benefits of consuming milk is osteoporosis prevention. Nutrients like calcium, vitamin D, and protein in milk act as raw materials for bone structure and enhance bone strength (Wallace et al., 2021).

Despite the numerous positive impacts of milk and dairy products on human society, dairy farmers face various problems and challenges. First, dairy cattle are blamed for the greenhouse gases emitted through enteric fermentation and the significant amount of manure excretion, which contribute to global warming and water pollution (Font-Palma, 2019). Additionally, the increasing global population and rising per capita income have led to a rapid increase in the demand for dairy products (Organization for Economic Co-operation and Development [OECD] & FAO, 2022). Other challenges include extreme weather conditions caused by climate change (Gauly & Ammer, 2020), rising labor costs and labor shortage (Wang et al., 2021), and the growing public concern for animal welfare. The industrialization of farming practices often aims to increase production by minimizing space and resources, but this approach raises the risk of animal diseases (e.g.,

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mastitis, lameness), which conflicts with contemporary ethical perspectives (Brombin et al., 2019; Henchion et al., 2022). Therefore, there is an urgent need to develop innovative systems for enhancing milk yield, while simultaneously mitigating negative environmental impacts and improving animal welfare, in other words, achieving sustainable development.

Smart dairy farming is a growing trend in dairy farms worldwide, involving the application of technologies such as the Internet of Things (IoT), big data, and artificial intelligence (AI) (Kulatunga et al., 2017; Nleya & Ndlovu, 2021). This approach utilizes IoT devices like sensors and robots to gather data on the farm environment and animals. The collected data is then analyzed using AI to generate reports on operational conditions, enabling better decision-making and ultimately improving milk productivity. Moreover, the data can be used to detect anomalies and provide early warnings, facilitating prompt disease treatment and improving animal health (Akbar et al., 2020; Bovo et al., 2020; Nleya & Ndlovu, 2021). In particular, one crucial function of AI in smart dairy farming is milk yield prediction. By obtaining estimated milk yield in advance, farmers can project their income and costs, optimize breeding selections and culling decisions, and enhance animal health monitoring (Liseune et al., 2020, 2021). Consequently, developing machine learning models with high prediction accuracy becomes a paramount task in this field.

This study aimed to develop accurate machine learning models to predict the daily milk yield of individual dairy cows. Various machine learning algorithms were employed to build prediction models using data obtained from dairy farms in Taiwan. Finally, the best model with the most accurate prediction was propose.

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Background

A. Cattle Milk Production in France, Japan, and Taiwan

The dairy industry plays a significant role in the global economy, with cattle milk accounting for about 81% of total milk production (OECD-FAO, 2022). Dairy cattle farms vary from country to country, influenced by geography, climate, society, economics, and culture, resulting in diverse outcomes in milk production (Chiu, 2009). The following section provides an overview of cattle milk production in France, Japan, and Taiwan in 2020. Detailed numerical data are shown in Appendix A.

1. France

The dairy industry in France holds a significant position in the country's economy and culinary culture. It also maintains competitiveness in the international market. France, being one of the world's largest dairy producers and exporters (Appendix B), annually produces 25 million tons of cattle milk (FAO, n.d.). With over 50,000 dairy farms, predominantly family-owned, the average farm raises 68 heads of cattle. Approximately 10% of dairy farms are equipped with automatic milking robots, and 160 farms have automatic feeding systems. The total number of dairy cattle in France is 3.4 million, with an average yield of 7,409 kg per cow per year. The three main breeds of dairy cows in France are Prim'Holstein, Montbéliarde, and Normande (Agreste, 2022; "À l'heure du lait", n.d.; Eurostat, n.d.; FAO, n.d.; Ministère de l'Agriculture et de la Souveraineté alimentaire, 2022). France's overall temperate climate, abundant rainfall, and ample farmland create favorable conditions for dairy farming, resulting in lower farming costs and a corresponding low milk price of USD 1.14 per liter (Numbeo, n.d.). Furthermore, the country's vast agricultural land with diverse climatic and soil conditions across different regions contributes to the wide variety of French dairy products ("À l'heure du lait", n.d.). Additionally, the

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French dairy industry emphasizes sustainable practices and environmental conservation, with many farmers adopting organic farming methods to maintain a balanced and harmonious relationship with nature (“À l'heure du lait”, n.d.).

2. *Japan*

The dairy industry in Japan plays an essential role in the country's agricultural sector, meeting domestic demand for a wide range of milk and dairy products. There are 14,400 dairy farms in Japan, with an average of 58 cows per farm, producing about 7.4 million tons of milk in total annually. The majority of the 839,000 dairy cows in Japan are Holstein cattle (Ministry of Agriculture, Forestry and Fishery [MAFF], 2023). Most dairy farms are family-run, while about 3% of farms are equipped with automatic milking robots (Japan Dairy Council, n.d.; 酪農 PLUS+, 2020). Due to Japan's mountainous and forested areas, land availability for dairy farming is limited, posing challenges for farm construction and land use. Efforts have been made to overcome these constraints, primarily by focusing on improving milk yield (Japan Dairy Council, n.d.). The annual average yield in 2020 reached 8,866 kg per cow. Importantly, consumer preferences greatly influence the Japanese dairy market, leading to a reliance on imports to satisfy the diverse consumer demands. However, domestic production remains crucial in meeting overall dairy demand in the country (MAFF, 2023). In terms of dairy product research and development, there is a focus on developing new flavors and textures, enhancing formulations, and improving nutritional value (Japan Livestock Products Export Promotion Council [J-LEC], n.d.).

3. *Taiwan*

Due to the development of farming techniques, milk production in Taiwan has been steadily increasing each year, reaching 437 thousand tons in 2020. With approximately 560 dairy farms in the country, each farm has an average of 113 cows.

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The Holstein breed is predominant, and the average milk yield is 6,937 kg per cow per year (Council of Agriculture, 2021; U.S. Department of Agriculture [USDA], 2022). However, the dairy industry in Taiwan faces challenges due to its natural environment. The climate is characterized by high temperatures and humidity, and the small land area and mountainous terrain further compound these challenges. Consequently, Taiwanese dairy farms have lower yields and are more susceptible to diseases compared to major milk-producing countries with more favorable climates and larger land areas. To mitigate the effects of the climate, Taiwanese dairy farms require additional cooling facilities, leading to increased operational costs. Moreover, the industry is facing labor shortages and high labor costs, which contribute to overall expenses; however, the adoption rate of automatic systems in farms is relatively low. Additionally, Taiwan heavily relies on imported feed ingredients, resulting in a low self-sufficiency ratio and additional cost burdens (Foodnext, 2022). As a result, the milk price in Taiwan remains relatively high, currently standing at USD 3.05 per liter (Numbeo, n.d.). To address these challenges, the Taiwanese dairy industry urgently needs to focus on farm automation, as well as breeding cattle that are well-adapted to the hot and humid weather conditions.

B. Smart Dairy Farming

Technology has had a significant and positive impact on dairy farming. For instance, automatic techniques are used for various dairy farming processes like recording the activity and behavior of individual animals, feeding, detecting estrus, milking, recording the yields of milk, monitoring milk quality, measuring the animals' body weights, and detecting diseases (Hsu, 2019; Nleya & Ndlovu, 2021). When this information is analyzed, integrated, and applied to decision making, it is referred to as smart dairy

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farming (Hsu, 2019). Smart dairy farming, also known as precision dairy farming, combines precision farming techniques with IoT, big data analytics, and cloud computing to enhance productivity in the dairy industry (Kulatunga et al., 2017). Smart dairy farming is undoubtedly a growing market nowadays. For example, the milking robots market size was USD 1.25 billion in 2019 and is projected to reach USD 2.94 billion in 2027 (Fortune Business Insights, 2020); the livestock monitoring market was worth USD 1.6 billion in 2022, and it is expected to reach USD 3.7 billion by 2030 (Markets and Markets, 2022).

Smart dairy farming comprises 4 major elements: environmental control, single animal information, automation of rearing work, and management (Nleya & Ndlovu, 2021). It is important to note that in this study, the focus is primarily on dairy cattle farms when discussing the dairy industry.

1. Environmental control

Heat stress is one of the main factors affecting the production efficiency of dairy cattle. Heat accumulation in the environment causes cows' body temperature to rise, resulting in reduced feed intake and ultimately leading to decreased performance, morbidity, and mortality (Fournel et al., 2017; Kadzere et al., 2002; West, 2003). Heat stress is caused by a combination of environmental factors, including temperature, relative humidity, solar radiation, air movement, and precipitation (Bohmanova et al., 2007). A variety of indices are used to estimate the degree of heat stress affecting dairy cattle. The most common of these is the temperature-humidity index (THI), using the combined effects of air temperature and humidity to quantify the magnitude of heat stress (Bohmanova et al., 2007). A variety of indices are used to estimate the degree of heat stress affecting dairy cattle. The most common of these is the temperature-humidity index (THI), using the combined effects of air temperature and

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humidity to represent the magnitude of heat stress (Bohmanova et al., 2007; Dikmen & Hansen, 2009; Ji et al., 2020).

Considering the great impact of heat stress on dairy cattle, the implementation of cooling systems in dairy farms is crucial. Common cooling facilities in dairy farms are shades, sprinklers, fans, and foggers (Collier et al., 2006). Studies have demonstrated the effectiveness of cooling systems in reducing heat stress in dairy cows (Bucklin et al., 1991; Buffington et al., 1983; Frazzi et al., 2000). However, traditional cooling systems operate on fixed time cycles (Armstrong, 1994; Flamenbaum & Galon, 2010), leading to potential unnecessary usage (Moretti et al., 2017). In smart dairy farming, the integration of IoT temperature and humidity sensors enables cooling systems to be automatically activated when real-time calculations indicate high heat stress levels, thus enhancing cooling efficiency and reducing energy costs (Goswami, 2020; Moretti et al., 2017; Vitali et al., 2009).

2. *Single Animal Information*

Recording individual information about cattle enhances herd management by improving animal welfare monitoring, disease control, and vaccination monitoring. Therefore, efficient and secure cattle identification systems are necessary to track relevant features for each cow over time (Awad, 2016; Qiao et al., 2021).

Traditional identification methods, which are marking body parts like ear notching, ear tattooing, hot iron branding, and freeze branding, have several common disadvantages, including low accuracy, causing discomfort in animals, and the possibility to be damaged or altered (Awad, 2016; Johnston & Edwards, 1996; Schwartzkopf-Genswein et al., 1997). Radio Frequency Identification (RFID) devices emerged later, which are electronic tools that enable wireless data transmission and

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remote animal identification (Ruiz-Garcia & Lunadei, 2011; Stankovski et al., 2012). An RFID system consists of RFID tags, RFID readers, and a management server. There are different types of RFID tags: ear tags, glass tags injected under the animals' skin, and boluses, which are acid-resistant capsules ingested by the animals (Awad, 2016; Ruiz-Garcia & Lunadei, 2011; Voulodimos et al., 2010). When an animal with an RFID tag gets near the reader, its individual information is transmitted to the reader by radio waves (Qiao et al., 2021) and then to the management server. This enables farmers to identify the specific cow near the reader, in other words, the gate, the feeding area, the milking area, or any other location where the reader is installed.

In addition, both attached and non-attached IoT sensors significantly enhance farm management by effectively and efficiently monitoring key health parameters of cattle such as body temperature, ruminal pH, heart rate, and respiration rate (Sharma & Koundal, 2018). The body temperature can be measured using attached sensors on the ear tag or collar (Darwis et al., 2022; Xia et al., 2020), rumen or reticular boluses (Bewley & Schutz, 2010; Lees et al., 2019), or infrared cameras in the surroundings (Schaefer et al., 2012). Boluses with pH sensors are used to monitor ruminal pH (Sato et al., 2012), while pulse sensors on belts or in boluses are employed for measuring heart rate (Smith et al., 2006). Several devices have been developed for measuring the respiration rate of cattle, including sensors fixed on chest belts for detecting thoracic and abdominal movements (Eigenberg et al., 2000; Martinez et al., 2006), sensors monitoring temperature or pressure differences near nostrils (Milan et al., 2016; Strutzke et al., 2019), and non-contact radar sensors that detect flank movements in cattle (Tuan et al., 2022).

Sensors can also be utilized for monitoring cattle behaviors. Ungar et al. (2005) employed GPS collars to track the positions of cattle and classify their grazing,

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traveling, and resting behaviors. Zehner et al. (2016) and Ruuska et al. (2016) developed a pressure-based noseband sensor to measure rumination, eating, and drinking behaviors. Gokul and Tadepalli (2017) applied wearable microphone sensors to detect mooing sounds, while Tran et al. (2022) developed leg-mounted and collar-mounted accelerometers to classify whether a cow was standing, lying, eating, or walking. Changes in these physiological and behavioral parameters can indicate health issues such as heat stress or lameness in cows. Hence, by continuously gathering data from sensors, farmers can promptly respond to any potential health issues.

In smart dairy farming, another trend in identification and monitoring is image recognition. By utilizing cameras or other photography equipment, noncontact animal identification can be done quickly and easily based on biometrics extracted from image data (Weng et al., 2022). Several physiological traits have been used for identification, including muzzle patterns (Barry et al., 2007; Kumar et al., 2018; Kumar et al., 2017; Kusakunniran et al., 2018), iris patterns (Awad et al., 2013; Larregui et al., 2019; Lu et al., 2014; Sun et al., 2013), retinal vascular patterns (Allen et al., 2008), coat patterns (Andrew et al., 2016; Okura et al., 2019), and facial appearance (Kim et al., 2005; Kumar et al., 2015; Wang et al., 2020; Weng et al., 2022; Yao et al., 2019). These features are captured through computer vision, converted into digital data, and analyzed using machine learning algorithms, allowing for rapid and highly accurate individual identification (Wu et al., 2021). Once an animal is identified, the computer vision can further record and recognize cattle behaviors like eating, standing, and lying also by machine learning (Avanzato et al., 2022; Porto et al., 2013, 2015), which again is useful information for cattle health management.

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3. *Automation of Rearing Work*

Dairy farmers often face time-consuming tasks such as milking, feeding, and cleaning. To enhance operational efficiency and reduce labor requirements, automatic cow-rearing systems have been developed. Among them, automatic milking systems are widely used in smart dairy farms, which have been proven to increase milk yield by 12%, reduce labor by 18%, and improve animal welfare by allowing cows to determine when they want to be milked (Jacobs & Siegford, 2012). An automatic milking system, also known as a milking robot, consists of various modules: milking stall, teat sensing system, teat cleaning system, robotic arm for attaching teat cups, milking machine, milk cooling system, and quality control system (de Koning, 2011; Klungel et al., 2000; Rossing & Hogewerf, 1997).

When a cow approaches the robot, its identity is detected, and feed is provided in the milking stall to keep the cow engaged during the process. The milking process begins, and important information is recorded, including body weight, milking frequency, milk yield, and various milk quality parameters such as temperature, fat content, protein content, total bacteria count (TBC), somatic cell count (SCC), color, and electrical conductivity. These measurements not only help assess individual productivity but also serve as indicators for disease detection, such as mastitis (de Koning, 2011; Hsu, 2019; Rossing & Hogewerf, 1997). Moreover, if any anomalies are detected, the robot automatically separates the affected batch of milk from the rest to prevent contamination and maintain milk quality (Hsu, 2019).

Automatic sorting gates are commonly integrated with automatic milking systems. Sorting gates are equipped with identification devices like RFID readers, and they can direct each cow to different areas based on their specific circumstances. One option is to place a sorting gate before the automatic milking system to identify cows

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that have recently been milked and redirect them to another area. Another option is to position a sorting gate after the automatic milking system to guide cows that require examination or treatment to an isolation area (Hsu, 2019; Laurs & Priekulis, 2008).

Precision feeding is an important component in smart dairy farming, meaning to provide each cow with specific amounts of nutrients that maximize productivity, reduce greenhouse gases emission, reduce waste production, or achieve any desired outcomes (Adviento-Borbe et al., 2010; Erickson & Kalscheur, 2020). Aside from the goal above, various factors influence the nutritional requirements of cows, including individual characteristics, milk yield, stage of lactation, pregnancy and parturition, and the amount of feed consumed during milking (Bach & Cabrera, 2017; Erickson & Kalscheur, 2020; Peyraud & Delagarde, 2013). Implementing automatic feeding systems is an efficient approach to achieve precision feeding with minimal labor (Monteiro et al., 2021). These systems automatically weigh and thoroughly mix dietary ingredients such as forage, grain, and supplements like minerals, vitamins, and proteins to create a total mixed ration (TMR), which is then distributed to each cow by robots (Coppock et al., 1981; Da Borso et al., 2017; Erickson & Kalscheur, 2020; Šístkova et al., 2015). Additionally, feed pusher robots can work in conjunction with the automatic feeding system, moving along the feeding passage and pushing feed towards the cows to minimize feed loss and ensure consistent feed intake (Nabokov et al., 2020).

4. *Management*

Dairy farm management is greatly enhanced by the facilities, devices, and systems mentioned above, particularly animal health management. Changes in the cow's behavioral, physiological, and production variables act as a mirror to changes in the cow's health (Awasthi et al., 2016). For instance, heat stress in cattle is

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characterized by elevated body temperature and respiration rate, increased drinking and standing behaviors, and decreased feed intake, milk production, and milk quality (Becker et al., 2020; Idris et al., 2021; Nienaber & Hahn, 2007; Ratnakaran et al., 2016; Rhoads et al., 2009); lameness is associated with extended lying time and reduced eating time, rumination time, milk yield, and milking frequency (Antanaitis et al., 2021; Garvey, 2022; Warnick et al., 2001); mastitis results in higher somatic cell count, bacterial count, and milk conductivity, as well as decreased milk yield (Ruegg & Reinemann, 2002; Seegers et al., 2003). Smart dairy farms employ sensors, cameras, and automated systems to comprehensively monitor cattle health. Whenever abnormalities are detected, farmers receive notifications or alerts via mobile applications or herd management software on their computers, enabling prompt examinations or treatments (Cockburn, 2020; Islam & Scott, 2022). Therefore, cows suffer less pain, and animal welfare is improved.

Another main development in smart dairy farming is precision breeding. The key objectives of breeding in dairy farming include high productivity, good reproduction performance, optimal health, longevity, low environmental impact, and high stress tolerance (Berry, 2015). Precision breeding aims to enhance the precision of attaining these desired traits through breeding (Flint & Woolliams, 2008). Genomic selection has revolutionized this process by utilizing genomic estimated breeding values (GEBV) to make selection decisions, with GEBV representing the predicted effects of the entire genome on certain traits (Hayes et al., 2009). This allows breeders to have an estimated outcome before actual breeding, enabling them to choose the best combination of female cows and bull semen. Furthermore, estrus detection techniques are employed to improve breeding success rates and enhance reproductive efficiency by reducing calving intervals (Bekara et al., 2017). During estrus, changes in body

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temperature and increased activity occur (Firk et al., 2002; Mayo et al., 2019; Roelofs et al., 2005). These changes are detected by monitoring systems, which automatically send alerts. Consequently, farmers can determine the optimal timing for artificial insemination (Hsu, 2019).

In conclusion, smart dairy farming serves as a promising solution to the challenges faced by the milk production industry today. Firstly, by incorporating techniques such as animal health monitoring, precision feeding, precision breeding, and automatic rearing systems, smart dairy farming can increase milk production and improve animal welfare simultaneously (Akbar et al., 2020; Bovo et al., 2020; Nleya & Ndlovu, 2021). Secondly, precision feeding and precision breeding practices contribute to the reduction of negative environmental impacts by decreasing greenhouse gas and manure emissions through feed and nutrition adjustments and selective cattle breeding (de Haas et al., 2011; Gerber et al., 2013; Hayes et al., 2013; Niloofar et al., 2021). Thirdly, regarding future climate change concerns, precision breeding enables the efficient selection of cattle breeds with high stress tolerance, while the implementation of cooling systems in dairy farms helps mitigate heat stress among cattle (Bucklin et al., 1991; Buffington et al., 1983; Frazzi et al., 2000; Hayes et al., 2013). Lastly, to address labor shortages and rising labor costs, automatic rearing systems have been proven to reduce labor requirements on dairy farms (Jacobs & Siegford, 2012). As a result, smart dairy farming undoubtedly contributes significantly to sustainable development.

C. Milk Yield Prediction

According to previous statements, it is clear that milk yield prediction is an essential component in smart dairy farming. In farm management, estimated milk production serves as an indicator of farm income. When it comes to animal health monitoring,

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differences between predicted milk yield and actual yield are utilized to identify potential diseases. Moreover, in precision breeding, estimated milk productivities provide insights into the performance of offspring resulting from various combinations of female cows and bull semen (Liseune et al., 2020).

The basic principle of milk yield prediction involves using historical data to establish a relationship between milking characteristics and milk yield that can estimate the future milk yield. Important factors that directly or indirectly influence milk yield include days of lactation, age, fertility, the season of calving, and climatic conditions, as well as genetics, weight, season of birth, parity, past performance, feed nutritional information, and milk quality (Lacroix et al., 1995; Murphy et al., 2014; Sharma et al., 2007; Smith, 1968; Wood, 1967).

However, in the early stages, milk yield prediction models focused solely on the relationship between days of lactation and milk yield, also known as the lactation curve. A lactation curve can be described as a function of time, characterized by a rapid increase until reaching a peak yield, followed by a steadier decline (Liseune et al., 2021; Olori et al., 1999). As early as the 1960s, Wood (1967) proposed an incomplete gamma function to fit the lactation curve. This formula has since been widely used in various models for predicting lactation yield (Grzesiak et al., 2006; Leon-Velarde et al., 1995; Schaeffer & Jamrozik, 1996). Other mathematical methods, such as polynomial functions and regression models, have also been employed to describe the shape of the lactation curve (Ali & Schaeffer, 1987).

Over time, with the advancement of technology and the availability of sensors, cameras, and automatic rearing systems, more animal records have been collected, leading to the development of new models with higher complexity that incorporate more

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input features (Cockburn, 2020; Liseune et al., 2021; Murphy et al., 2014). Multiple linear regression is a common statistical technique commonly used for building predictive models (Dongre et al., 2012; Grzesiak et al., 2003; Murphy et al., 2014; Sharma et al., 2006, 2007). Machine learning models have also proven useful for predicting milk yield, employing algorithms such as supported vector regression (SVR), random forest regression, extreme gradient boosting machine (XGBoost), long short-term memory (LSTM), and artificial neural network (ANN) (Dongre et al., 2012; Grzesiak et al., 2003; Hsieh et al., 2011; Ji et al., 2022; Nguyen et al., 2020; Zhang et al., 2020).

The implementation of these new models has resulted in significant improvements in performance. For instance, Lacroix et al. (1995) developed an ANN model that utilized 16 input variables, such as days of lactation, age, parity, season of calving, weight, feed nutrition, and milk quality information, achieving correlation coefficients ranging from 0.897 to 0.980; Sharma et al. (2007) utilized 12 traits (genetic group, season of birth, period of birth, birth weight, age at maturity, weight at maturity, season of calving, period of calving, age at calving, weight at calving, peak yield, and days to attain peak yield) to build an ANN model, achieving over 92% prediction accuracy.

Materials and Methods

A. Data Sources

The Dairy Herd Improvement (DHI) project in Taiwan aims to collect, preserve, and analyze dairy cow information. Its purpose is to provide dairy farmers with reports to aid in their management decisions and assist relevant units in evaluating the genetic ability of Taiwanese cattle for milk production. The data are collected once a month (Council of Agriculture, 2003; Chang et al., 2001). For this study, four data sets originated from the DHI project were downloaded from the online competition "Prediction of Milk Yield of

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Taiwan Ranches" on the Artificial Intelligence Collaboration Platform (https://aidea-web.tw/topic/fcc338da-e7ec-4d9e-a860-5dcdd85ba52b?lang=en). The main data set contains 37,517 milking records among 1,991 Holstein cattle across three dairy farms in Taiwan, spanning from 2013 to 2019. Additionally, three other data sets are breeding records (n=21,050), calving records (n=3,761), and health records (n=4,362). Weather information was obtained from the Observation Data Inquire System of the Central Weather Bureau (http://e-service.cwb.gov.tw/HistoryDataQuery/index.jsp).

B. Data Processing

All programming processes were done using Python code within a Jupyter notebook under a virtual environment in Anaconda (https://github.com/guanguan-chen/Milk-Yield-Prediction_Taiwanese-Data/tree/Version-2).

1. Data Cleaning

Initially, the data cleaning process involved removing rows from the main dataset that had missing values for any of the following variables: *year*, *month*, *farm code*, *parity*, *days of lactation*, *age in months*, or *milk yield*. Additionally, rows with *milk yield* of 0 were also eliminated. The resulting cleaned dataset consisted of 33,185 milking records from 1,818 cows across three dairy farms, spanning from 2013 to 2018. The objective was to develop models using data from 2013 to 2017 and predict daily milk yield for 2018, simulating the prediction of milk yield for the following year using historical data up until the current year. Therefore, when constructing the models, the data from 2018 was excluded, and the remaining data was split into two parts: 80% for training and 20% for validation. The initial feature combination (F1) consisted of five original features: *month*, *farm code*, *parity*, *days of lactation*, and *age in months*.

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2. *Feature Generation*

The main dataset provided information on the month, birth date, and latest calving date, allowing for the generation of new variables: *milking season*, *birth season*, and *calving season*. Additionally, *calving interval* and *if first calving* were derived from parity, previous calving date, and latest calving date. To represent productivity, *average yield* was calculated using past records (from 2013 until the end of the previous year) for each cow. Any missing values were imputed with the mean of all milk yield records. These new features plus F1 were the second feature combination (F2).

From the birth dataset, *dry period* and *hardness of calving* were generated and incorporated into the main dataset. The dry period refers to the time span before the next calving when a cow stops producing milk. It was included in the records for the subsequent parity. The third feature combination (F3) comprised the *dry period*, *hardness of calving*, and F2. Furthermore, *situation type* and *situation code* were added to the main dataset from the health dataset. Situation codes represented different reasons causing specific types of situations. These two features, along with F3, constituted the fourth feature combination (F4). Finally, temperature and relative humidity (RH) information for each day on each farm was included. The temperature-humidity index (THI) was calculated using the formula below, which helped determine the level of heat stress: no stress (THI < 72), mild stress ($72 \leq$ THI < 80), moderate stress ($80 \leq$ THI < 90), and severe stress (THI ≥ 90) (Armstrong, 1994). Along with F4, these four weather-related features formed the fifth feature combination (F5), resulting in a total of 19 features.

$$THI = (1.8 \times T + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times T - 26.8)$$

(Dikmen & Hansen, 2009)

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C. Machine Learning Models

Before proceeding, missing values in the dataset were imputed using the median of each column. Categorical variables were then converted into numerical ones using one-hot encoding, which involves creating a binary column for each category. Then, three supervised learning algorithms, namely support vector regression (SVR) from support vector machine (SVM), random forest (RF), and extreme gradient boosting machine (XGBoost, XGB), were used to build models using F1 to F5. In the final step, hyperparameter tuning was performed on each model using grid search, which involves exploring all possible combinations of parameter values to identify the best-performing one. The tuned model with the highest accuracy for each algorithm was then used to predict the data for the year 2018.

Results

A. Model Performance

Figure 1 shows the accuracies of SVR, RF, and XGB models built with F1 to F5 and F5 (tuned). Significant increases in F2 and F5 (tuned) and slight decreases in F5 are observed. The SVR, RF, and XGB model accuracies of F5 (tuned) were 77.18%, 78.64%, and 80.21%, while the prediction accuracies on data in 2018 are 74.68%, 75.95%, and 76.33%, respectively. Detailed values of the results are shown in Appendix C.

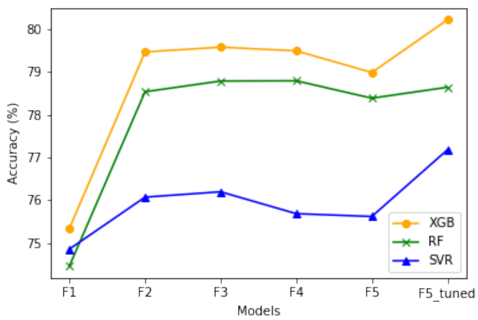

Figure 1. Model accuracies

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B. Important Features

The top 20 features with the highest feature importance of the XGBoost model using F5 (tuned) are shown in Figure 2. The top 4 are *average yield*, *days of lactation*, *calving interval*, and *age in months*.

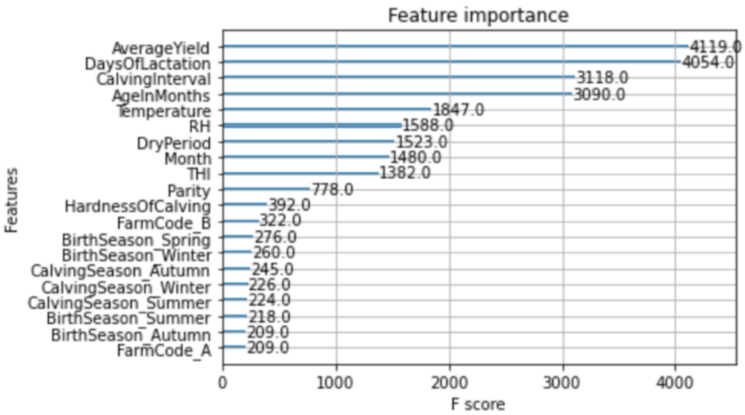
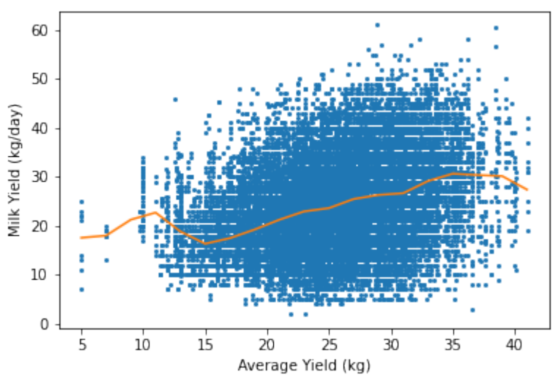


Figure 2. Top 20 important features in the XGBoost model using F5 (tuned)

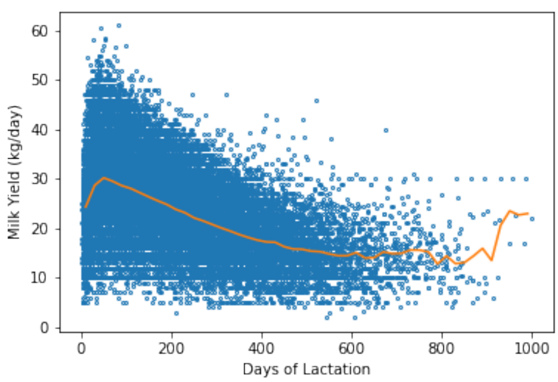
C. Relationship Between Milk Yield and the Top Four Important Features

Figure 3a to 3d illustrate the relationship between *milk yield* and *average yield*, *days of lactation*, *calving interval*, and *age in months*. Notably, there is a positive correlation between *milk yield* and *average yield* (Figure 3a). As depicted in Figure 3b, milk yield reaches its peak around the 50th day of lactation and gradually declines thereafter. Figure 3c does not reveal any clear patterns. Additionally, Figure 3d suggests that cattle at 35 months of age exhibited the highest mean milk yield.

a



b



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c d

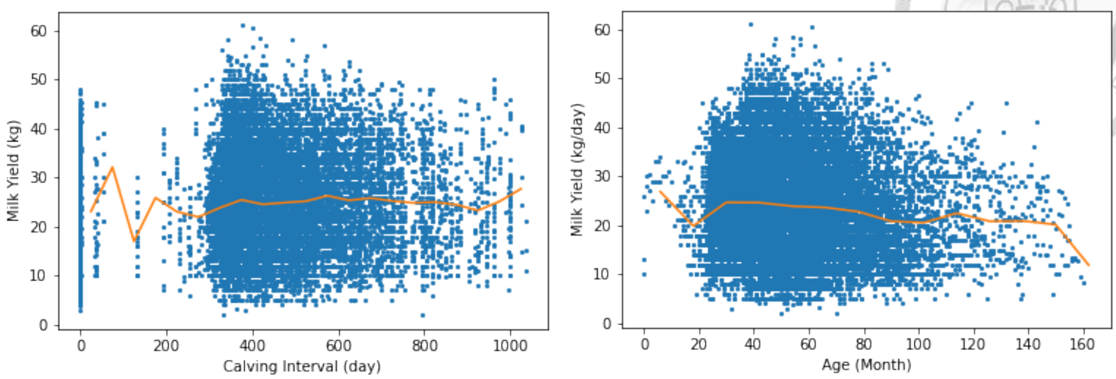

Figure 3. Relationship between milk yield and the top 4 important features. (a) Relationship between milk yield average yield. (d) Relationship between milk yield and days of lactation. (e) Relationship between milk yield and calving interval. (f) Relationship between milk yield and age in months. The orange lines are the mean curves.

Discussion

In this study, machine learning models were built to predict milk yield. The effectiveness of a milk yield prediction model depends on its ability to capture patterns and adjust factors affecting milk yield (Murphy et al., 2014). Figure 1 shows a significant improvement in accuracy for models incorporating F2, indicating a strong correlation between at least one of the new features in F2 and milk yield. Based on the important features identified (Figure 2), it is evident that the inclusion of *average yield* and *calving interval* significantly contributes to the increased accuracy. Additionally, the increases in accuracies observed in models built with F5 (tuned) highlight the effectiveness of hyperparameter tuning. Among all the models evaluated, the XGBoost algorithm demonstrated the highest prediction accuracy, achieving an impressive 76.33%.

The top four significant factors influencing milk yield were identified as *average yield*, *days of lactation*, *calving interval*, and *age in months* (Figure 2, 3). This study introduces *average yield* as a novel feature, which is found to be the primary determinant

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of milk yield. Despite the absence of genetic information, past performance appears to indirectly reflect the individual cow's standard performance. Wood (1967) declared that the general shape of a single lactation curve remains substantially unchanged and proposed an algebraic equation to fit the curves, which has been widely applied by others (Grzesiak et al., 2006; Leon-Velarde et al., 1995; Schaeffer & Jamrozik, 1996). The mean curve of milk yield throughout the lactation period in this study aligns with the curve that Wood (1967) proposed (Appendix D), proving that indeed the milk yield follows a consistent pattern during the lactation period. Traditionally, the calving interval is around 12 to 13 months (Arbel et al., 2001), determined by the calving-to-conception interval (days open) and the dry period. However, *dry period* in this study was not as influential as *calving interval*, possibly due to insufficient information on dry period dates in the original dataset. In addition, 3- to 6-year-old cows had the highest milk yield peak and sustained relatively higher production compared to younger or older cows (Appendix E).

The importance of weather-related features emerged as follows: Temperature, relative humidity (RH), month, and temperature-humidity index (THI) ranked as the 5th, 6th, 8th, and 9th significant features (Figure 1), indicating their impact on milk yield, albeit indirectly. Several reasons could explain this. The weather information was collected from observation stations near the farms, potentially introducing errors compared to true farm values. Factors like wind speed, aside from temperature and relative humidity, may also influence heat stress levels. Additionally, the chosen formula may not accurately reflect the severity of heat stress in this study.

Despite the promising results of the prediction models in this study, there are still limitations. Firstly, the data sets were not thoroughly cleaned, containing unreasonable values such as unusually high numbers for days of lactation and calving interval. However, without the ability to contact the data providers, it was challenging to address these issues

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appropriately. Secondly, the health condition of cows should be considered as an influential factor for milk yield. However, the health data set lacked descriptions of situation types and codes, as well as the duration of each situation, since information was collected only once a month. Hence, the health information is not able to help with the learning of the models. Lastly, incorporating additional factors such as genetic group of cows, birth weight, age at maturity, weight at maturity and calving, as well as feed nutrition intake and milk quality, could significantly enhance the accuracy of milk yield prediction.

Conclusion

This study developed milk yield prediction models using 19 input variables. The best-performing model utilized XGBoost as the algorithm, demonstrated an accuracy of 76.33% in predicting future milk yield. The results indicated that average yield, days of lactation, calving interval, and age in months are the most important features affecting milk yield. Nevertheless, it is important to acknowledge that the models have certain limitations. To further improve prediction accuracy, future work should prioritize the implementation of a more comprehensive and frequent data collection system in dairy farms. This would ensure a more extensive dataset, allowing the models to capture the patterns of milk yield variations more effectively. Overall, the developed models represent a valuable step towards enhancing milk yield prediction in dairy farming.

doi:10.6342/NTU202303425

References

Adviento-Borbe, M. A. A., Wheeler, E. F., Brown, N. E., Topper, P. A., Graves, R. E., Ishler, V. A., & Varga, G. A. (2010). Ammonia and Greenhouse Gas Flux from Manure in Freestall Barn with Dairy Cows on Precision Fed Rations. *Transactions of the ASABE*, *53*(4), 1251-1266. https://doi.org/10.13031/2013.32590

Akbar, M. O., Shahbaz khan, M. S., Ali, M. J., Hussain, A., Qaiser, G., Pasha, M., Pasha, U., Missen, M. S., & Akhtar, N. (2020). IoT for Development of Smart Dairy Farming. *Journal of Food Quality*, *2020*, 4242805. https://doi.org/10.1155/2020/4242805

Agreste, Ministère de l'Agriculture et de l'Alimentation, France (2022). *Enquête annuelle laitière 2020* [Annual Dairy Survey 2020]. https://agreste.agriculture.gouv.fr/agreste-web/download/publication/publie/Chd2202/cd2022-02_EAL2020.pdf

À l'heure du lait (n.d.) https://www.ferme-laitiere-france.com/en/the-milk-files/

Ali, T. E., & Schaeffer, L. R. (1987). Accounting for covariances among test day milk yields in dairy cows. *Canadian Journal of Animal Science*, *67*(3), 637-644. https://doi.org/10.4141/cjas87-067

Allen, A., Golden, B., Taylor, M., Patterson, D., Henriksen, D., & Skuce, R. (2008). Evaluation of retinal imaging technology for the biometric identification of bovine animals in Northern Ireland. *Livestock Science*, *116*(1), 42-52. https://doi.org/10.1016/j.livsci.2007.08.018

Andrew, W., Hannuna, S., Campbell, N., & Burghardt, T. (2016). *Automatic individual holstein friesian cattle identification via selective local coat pattern matching in RGB-D imagery.* 2016 IEEE International Conference on Image Processing

doi:10.6342/NTU202303425

(ICIP), Phoenix, AZ, USA. https://doi.org/10.1109/ICIP.2016.7532404

Antanaitis, R., Juozaitienė, V., Urbonavičius, G., Malašauskienė, D., Televičius, M., Urbutis, M., & Baumgartner, W. (2021). Impact of Lameness on Attributes of Feeding Registered with Noseband Sensor in Fresh Dairy Cows. *Agriculture*, *11*(9). https://doi.org/10.3390/agriculture11090851

Arbel, R., Bigun, Y., Ezra, E., Sturman, H., & Hojman, D. (2001). The Effect of Extended Calving Intervals in High Lactating Cows on Milk Production and Profitability. *Journal of Dairy Science*, *84*(3), 600-608. https://doi.org/10.3168/jds.S0022-0302(01)74513-4

Armstrong, D. V. (1994). Heat Stress Interaction with Shade and Cooling. *Journal of Dairy Science*, *77*(7), 2044-2050. https://doi.org/10.3168/jds.S0022-0302(94)77149-6

Avanzato, R., Beritelli, F., & Puglisi, V. F. (2022). *Dairy Cow Behavior Recognition Using Computer Vision Techniques and CNN Networks.* 2022 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS), Bali, Indonesia. https://doi.org/10.1109/IoTaIS56727.2022.9975979

Awad, A. I. (2016). From classical methods to animal biometrics: A review on cattle identification and tracking. *Computers and Electronics in Agriculture*, *123*, 423-435. https://doi.org/10.1016/j.compag.2016.03.014

Awad, A. I., Zawbaa, H. M., Mahmoud, H. A., Nabi, E. H. H. A., Fayed, R. H., & Hassanien, A. E. (2013). *A robust cattle identification scheme using muzzle print images.* 2013 Federated Conference on Computer Science and Information Systems, Krakow, Poland.

Awasthi, A., Awasthi, A., Riordan, D., & Walsh, J. (2016). Non-Invasive Sensor Technology for the Development of a Dairy Cattle Health Monitoring System.

doi:10.6342/NTU202303425

Computers, *5*(4). https://doi.org/10.3390/computers5040023

Bach, A., & Cabrera, V. (2017). Robotic milking: Feeding strategies and economic returns. *Journal of Dairy Science*, *100*(9), 7720-7728. https://doi.org/10.3168/jds.2016-11694

Barry, B., A. Gonzales-Barron, U., McDonnell, K., Butler, F., & Ward, S. (2007). Using Muzzle Pattern Recognition as a Biometric Approach for Cattle Identification. *Transactions of the ASABE*, *50*(3), 1073-1080. https://doi.org/10.13031/2013.23121

Becker, C. A., Collier, R. J., & Stone, A. E. (2020). Invited review: Physiological and behavioral effects of heat stress in dairy cows. *Journal of Dairy Science*, *103*(8), 6751-6770. https://doi.org/10.3168/jds.2019-17929

Bekara, M. E. A., Bareille, N., Bidan, F., Allain, C., & Disenhaus, C. (2017). *An ex ante analysis of the economic profitability of automatic oestrus detection devices in different dairy farming systems in France.* European Conference on Precision Livestock Farming (ECPLF), Nantes, France. https://hal.science/hal-01591150

Berry, D. P. (2015). Breeding the dairy cow of the future: what do we need? *Animal Production Science*, *55*(7), 823-837. https://doi.org/10.1071/AN14835

Bewley, J. M., & Schutz, M. M. (2010). *Recent studies using a reticular bolus system for monitoring dairy cattle core body temperature.* The First North American Conference on Precision Dairy Management, Toronto, Canada. http://precisiondairy.com/proceedings/s11bewley.pdf

Bohmanova, J., Misztal, I., & Cole, J. B. (2007). Temperature-Humidity Indices as Indicators of Milk Production Losses due to Heat Stress. *Journal of Dairy Science*, *90*(4), 1947-1956. https://doi.org/10.3168/jds.2006-513

Bovo, M., Benni, S., Barbaresi, A., Santolini, E., Agrusti, M., Torreggiani, D., &

doi:10.6342/NTU202303425

Tassinari, P. (2020). *A Smart Monitoring System for a Future Smarter Dairy Farming.* 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Trento, Italy. https://doi.org/10.1109/MetroAgriFor50201.2020.9277547

Brombin, A., Pezzuolo, A., & Brščić, M. (2019). Are we ready for the big change in the dairy production system? *Research in Veterinary Science*, *126*, 17-19. https://doi.org/10.1016/j.rvsc.2019.08.006

Bucklin, R. A., Turner, L. W., Beede, D. K., Bray, D. R., & Hemken, R. W. (1991). Methods to Relieve Heat Stress for Dairy Cows in Hot, Humid Climates. *Applied Engineering in Agriculture*, *7*(2), 241-247. https://doi.org/10.13031/2013.26218

Buffington, D. E., Collier, R. J., & Canton, G. H. (1983). Shade Management Systems to Reduce Heat Stress for Dairy Cows in Hot, Humid Climates. *Transactions of the ASAE*, *26*(6), 1798-1802. https://doi.org/10.13031/2013.33845

Chang, C. L., Tseng, C. Y., Lee, S .J., Chen, J. Y., Huang, Y. C., Lee, S. C., Chang, H. L., & Wu, M. C. (2001). Dairy Herd Improvement (DHI) Program in Taiwan. *Taiwan Livestock Res., 34*(4), 285-295. https://www.angrin.tlri.gov.tw/cow/Twndhi.htm

Chiu, S. Y. (2009) *日本乳業概況系列（四）*[Overview of the Japanese Dairy Industry Series (Four)]. https://www.angrin.tlri.gov.tw/cow/dhi75/dhi75P30.htm

Cockburn, M. (2020). Review: Application and Prospective Discussion of Machine Learning for the Management of Dairy Farms. *Animals*, *10*(9). https://doi.org/10.3390/ani10091690

Collier, R. J., Dahl, G. E., & VanBaale, M. J. (2006). Major Advances Associated with Environmental Effects on Dairy Cattle. *Journal of Dairy Science*, *89*(4), 1244-

doi:10.6342/NTU202303425

1253. https://doi.org/10.3168/jds.S0022-0302(06)72193-2

Coppock, C. E., Bath, D. L., & Harris, B. (1981). From Feeding to Feeding Systems. *Journal of Dairy Science*, *64*(6), 1230-1249. https://doi.org/10.3168/jds.S0022-0302(81)82698-7

Council of Agriculture, Executive Yuan, Taiwan. (2003, June). *台灣地區乳牛群性能改良執行成效及檢討* [Implementation effectiveness and review of Dairy Herd Improvement in Taiwan]. https://www.coa.gov.tw/ws.php?id=4450

Council of Agriculture, Executive Yuan, Taiwan. (2021). *農業統計年報（109 年）* [AG. Statistic Yearbook 2020]. https://agrstat.coa.gov.tw/sdweb/public/book/Book.aspx

Da Borso, F., Chiumenti, A., Sigura, M., & Pezzuolo, A. (2017). Influence of automatic feeding systems on design and management of dairy farms. *Journal of Agricultural Engineering*, *48*(s1), 48-52. https://doi.org/10.4081/jae.2017.642

Darwis, D., Mehta, A. R., Wati, N. E., Samsugi, S., & Swaminarayan, P. R. (2022). *Digital Smart Collar: Monitoring Cow Health Using Internet of Things.* 2022 International Symposium on Electronics and Smart Devices (ISESD), Bandung, Indonesia. https://doi.org/10.1109/ISESD56103.2022.9980682

de Haas, Y., Windig, J. J., Calus, M. P. L., Dijkstra, J., de Haan, M., Bannink, A., & Veerkamp, R. F. (2011). Genetic parameters for predicted methane production and potential for reducing enteric emissions through genomic selection. *Journal of Dairy Science*, *94*(12), 6122-6134. https://doi.org/10.3168/jds.2011-4439

de Koning, C. J. A. M. (2011). Milking Machines | Robotic Milking. In J. W. Fuquay (Ed.), *Encyclopedia of Dairy Sciences (Second Edition)* (pp. 952-958). Academic Press. https://doi.org/10.1016/B978-0-12-374407-4.00360-5

Dikmen, S., & Hansen, P. J. (2009). Is the temperature-humidity index the best indicator

doi:10.6342/NTU202303425

of heat stress in lactating dairy cows in a subtropical environment? *Journal of Dairy Science*, *92*(1), 109-116. https://doi.org/10.3168/jds.2008-1370

Dongre, V. B., Gandhi, R. S., Singh, A., & Ruhil, A. P. (2012). Comparative efficiency of artificial neural networks and multiple linear regression analysis for prediction of first lactation 305-day milk yield in Sahiwal cattle. *Livestock Science*, *147*(1), 192-197. https://doi.org/10.1016/j.livsci.2012.04.002

Eigenberg, R., Hahn, G., Nienaber, J., Brown-Brandl, T., & Spiers, D. (2000). Development of a new respiration rate monitor for cattle. *Transactions of the ASAE*, *43*. https://doi.org/10.13031/2013.2755

Erickson, P. S., & Kalscheur, K. F. (2020). Chapter 9 - Nutrition and feeding of dairy cattle. In F. W. Bazer, G. C. Lamb, & G. Wu (Eds.), *Animal Agriculture* (pp. 157-180). Academic Press. https://doi.org/10.1016/B978-0-12-817052-6.00009-4

Eurostat (n.d.) *Number of dairy cows* [dataset]. https://ec.europa.eu/eurostat/databrowser/view/TAG00014/default/table?lang=en&category=agr.apro.apro_anip.apro_mt.apro_mt_ls

Firk, R., Stamer, E., Junge, W., & Krieter, J. (2002). Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, *75*(3), 219-232. https://doi.org/10.1016/S0301-6226(01)00323-2

Flamenbaum, I., & Galon, N. (2010). Management of Heat Stress to Improve Fertility in Dairy Cows in Israel. *Journal of Reproduction and Development*, *56*(S), S36-S41. https://doi.org/10.1262/jrd.1056S36

Flint, A. P., & Woolliams, J. A. (2008). Precision animal breeding. *Philos Trans R Soc Lond B Biol Sci*, *363*(1491), 573-590. https://doi.org/10.1098/rstb.2007.2171

Font-Palma, C. (2019). Methods for the Treatment of Cattle Manure—A Review.

doi:10.6342/NTU202303425

Journal of Carbon Research, *5*(2). https://doi.org/10.3390/c5020027

Food and Agriculture Organization of the United Nations [FAO]. (n.d.). FAOSTAT statistical database. https://www.fao.org/faostat/en/#data

Food and Agriculture Organization of the United Nations [FAO]. (2022). *Food Outlook – Biannual Report on Global Food Markets, November 2022*. https://doi.org/10.4060/cc2864en

Foodnext. (2022). *乳業戰爭 九大擂台誰是贏家* [Dairy War: Who are the Winners among the Nine Major Contenders?]. Foodnext Quarterly Publication, 26. https://www.cunext.asia/products/vol26

Fortune Business Insights. (2020). *Milking Robots Market Size, Share & Industry Analysis, By System Type (Single-Stall Unit, Multi-Stall Unit, Automated Milking Rotary), By Herd Size (Less than 100, 100-1000 and 1001 and Above), and Regional Forecast, 2020-2027*. https://www.fortunebusinessinsights.com/milking-robots-market-102996

Fortune Business Insights. (2022). *Dairy Foods Market Size, Share & COVID-19 Impact Analysis, By Source (Cattle, Sheep, Goat, and Camel), Type (Lactose and Lactose-free), Product Type (Milk, Cheese, Butter, Dessert, Yogurt, and Others), Distribution Channel (Supermarkets/Hypermarkets, Specialty Stores, Convenience Stores, and Online Retail), and Regional Forecast, 2021-2028*. https://www.fortunebusinessinsights.com/dairy-foods-market-103890

Fournel, S., Rousseau, A. N., & Laberge, B. (2017). Rethinking environment control strategy of confined animal housing systems through precision livestock farming. *Biosystems Engineering*, *155*, 96-123. https://doi.org/10.1016/j.biosystemseng.2016.12.005

Frazzi, E., Calamari, L., Calegari, F., & Stefanini, L. (2000). Behavior of Dairy Cows in

doi:10.6342/NTU202303425

Response to Different Barn Cooling Systems. *Transactions of the ASAE*, *43*(2), 387-394. https://doi.org/10.13031/2013.2716

Garvey, M. (2022). Lameness in Dairy Cow Herds: Disease Aetiology, Prevention and Management. *Dairy*, *3*(1), 199-210. https://doi.org/10.3390/dairy3010016

Gauly, M., & Ammer, S. (2020). Review: Challenges for dairy cow production systems arising from climate changes. *animal*, *14*(S1), s196-s203. https://doi.org/10.1017/S1751731119003239

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). *Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities*. Food and Agriculture Organization of the United Nations (FAO).

Gokul, V., & Tadepalli, S. (2017). *Implementation of smart infrastructure and non-invasive wearable for real time tracking and early identification of diseases in cattle farming using IoT.* 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India. https://doi.org/10.1109/I-SMAC.2017.8058394

Goswami, S. (2020). Temperature Based Automatic Cooling System for Livestock Farm in Western Region of Rajasthan using Arduino. *International Advanced Research Journal in Science, Engineering and Technology*, *7*(11). https://doi.org/10.17148/IARJSET.2020.71114

Grzesiak, W., Błaszczyk, P., & Lacroix, R. (2006). Methods of predicting milk yield in dairy cows—Predictive capabilities of Wood's lactation curve and artificial neural networks (ANNs). *Computers and Electronics in Agriculture*, *54*(2), 69-83. https://doi.org/10.1016/j.compag.2006.08.004

Grzesiak, W., Lacroix, R., Wójcik, J., & Blaszczyk, P. (2003). A comparison of neural

doi:10.6342/NTU202303425

network and multiple regression predictions for 305-day lactation yield using partial lactation records. *Canadian Journal of Animal Science*, *83*(2), 307-310. https://doi.org/10.4141/A02-002

Hayes, B. J., Bowman, P. J., Chamberlain, A. J., & Goddard, M. E. (2009). Invited review: Genomic selection in dairy cattle: Progress and challenges. *Journal of Dairy Science*, *92*(2), 433-443. https://doi.org/10.3168/jds.2008-1646

Hayes, B. J., Lewin, H. A., & Goddard, M. E. (2013). The future of livestock breeding: genomic selection for efficiency, reduced emissions intensity, and adaptation. *Trends in Genetics*, *29*(4), 206-214. https://doi.org/10.1016/j.tig.2012.11.009

Henchion, M. M., Regan, Á., Beecher, M., & MackenWalsh, Á. (2022). Developing 'Smart' Dairy Farming Responsive to Farmers and Consumer-Citizens: A Review. *Animals*, *12*(3). https://doi.org/10.3390/ani12030360

Hsieh, C.-L., Hung, C.-Y., & Kuo, C.-Y. (2011). *Quantization of Adulteration Ratio of Raw Cow Milk by Least Squares Support Vector Machines (LS-SVM) and Visible/Near Infrared Spectroscopy.* Engineering Applications of Neural Networks, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-23957-1_15

Hsu, J. (2019). Benefit analysis of dairy farm automation and smart system employment. *Journal of the Agricultural Association of Taiwan*, *20*(1), 39-58. https://doi.org/10.6730/JAAT.201903_20(1).0004

Idris, M., Uddin, J., Sullivan, M., McNeill, D. M., & Phillips, C. J. C. (2021). Non-Invasive Physiological Indicators of Heat Stress in Cattle. *Animals*, *11*(1). https://doi.org/10.3390/ani11010071

International Dairy Federation [IDF]. (2019). *The Global Dairy Sector: Facts 2019*. http://www.dairydeclaration.org/Portals/153/Content/Documents/DDOR%20Global%20Dairy%20Facts%202019.pdf

doi:10.6342/NTU202303425

Islam, M. M., & Scott, S. D. (2022). *Exploring the Effects of Precision Livestock Farming Notification Mechanisms on Canadian Dairy Farmers*. Science and Technologies for Smart Cities, Cham. https://doi.org/10.1007/978-3-031-06371-8_16

Jacobs, J. A., & Siegford, J. M. (2012). Invited review: The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science*, *95*(5), 2227-2247. https://doi.org/10.3168/jds.2011-4943

Japan Dairy Council (n.d.). *Japan Dairy Farming*. https://www.dairy.co.jp/jp/engall.pdf

Japan Livestock Products Export Promotion Council [J-LEC]. (n.d.). *The Feature: Milk and Dairy Products*. http://jlec-pr.jp/en/milk/milk-tokutyou/

Ji, B., Banhazi, T., Ghahramani, A., Bowtell, L., Wang, C., & Li, B. (2020). Modelling of heat stress in a robotic dairy farm. Part 1: Thermal comfort indices as the indicators of production loss. *Biosystems Engineering*, *199*, 27-42. https://doi.org/10.1016/j.biosystemseng.2019.11.004

Ji, B., Banhazi, T., Phillips, C. J. C., Wang, C., & Li, B. (2022). A machine learning framework to predict the next month's daily milk yield, milk composition and milking frequency for cows in a robotic dairy farm. *Biosystems Engineering*, *216*, 186-197. https://doi.org/10.1016/j.biosystemseng.2022.02.013

Johnston, A. M., & Edwards, D. S. (1996). Welfare implications of identification of cattle by ear tags [10.1136/vr.138.25.612]. *Veterinary Record*, *138*(25), 612-614. https://doi.org/10.1136/vr.138.25.612

Kadzere, C. T., Murphy, M. R., Silanikove, N., & Maltz, E. (2002). Heat stress in lactating dairy cows: a review. *Livestock Production Science*, *77*(1), 59-91. https://doi.org/10.1016/S0301-6226(01)00330-X

Kim, H. T., Ikeda, Y., & Choi, H. L. (2005). The Identification of Japanese Black Cattle

doi:10.6342/NTU202303425

by Their Faces. *Asian-Australas J Anim Sci*, *18*(6), 868-872. https://doi.org/10.5713/ajas.2005.868

Klungel, G. H., Slaghuis, B. A., & Hogeveen, H. (2000). The Effect of the Introduction of Automatic Milking Systems on Milk Quality1. *Journal of Dairy Science*, *83*(9), 1998-2003. https://doi.org/10.3168/jds.S0022-0302(00)75077-6

Kulatunga, C., Shalloo, L., Donnelly, W., Robson, E., & Ivanov, S. (2017). Opportunistic Wireless Networking for Smart Dairy Farming. *IT Professional*, *19*(2), 16-23. https://doi.org/10.1109/MITP.2017.28

Kumar, S., Pandey, A., Sai Ram Satwik, K., Kumar, S., Singh, S. K., Singh, A. K., & Mohan, A. (2018). Deep learning framework for recognition of cattle using muzzle point image pattern. *Measurement*, *116*, 1-17. https://doi.org/10.1016/j.measurement.2017.10.064

Kumar, S., Singh, S. K., & Singh, A. K. (2017). Muzzle point pattern based techniques for individual cattle identification. *IET Image Processing*, *11*(10), 805-814. https://doi.org/10.1049/iet-ipr.2016.0799

Kumar, S., Tiwari, S., & Singh, S. K. (2015). *Face recognition for cattle.* 2015 Third International Conference on Image Information Processing (ICIIP), Waknaghat, India. https://doi.org/10.1109/ICIIP.2015.7414742

Kusakunniran, W., Wiratsudakul, A., Chuachan, U., Kanchanapreechakorn, S., & Imaromkul, T. (2018). *Automatic cattle identification based on fusion of texture features extracted from muzzle images.* 2018 IEEE International Conference on Industrial Technology (ICIT), Lyon, France. https://doi.org/10.1109/ICIT.2018.8352400

Lacroix, R., M. Wade, K., Kok, R., & F. Hayes, J. (1995). Prediction of Cow Performance with a Connectionist Model. *Transactions of the ASAE*, *38*(5),

doi:10.6342/NTU202303425

1573-1579. https://doi.org/10.13031/2013.27984

Larregui, J. I., Cazzato, D., & Castro, S. M. (2019). An image processing pipeline to segment iris for unconstrained cow identification system. *9*(1), 145-159. https://doi.org/10.1515/comp-2019-0010 (Open Computer Science)

Laurs, A., & Priekulis, J. (2008). Robotic milking of dairy cows. *Agronomy Research*, *6*, 241–247. https://agronomy.emu.ee/vol06Spec/p6S08.pdf

Lees, A. M., Sejian, V., Lees, J. C., Sullivan, M. L., Lisle, A. T., & Gaughan, J. B. (2019). Evaluating rumen temperature as an estimate of core body temperature in Angus feedlot cattle during summer. *International Journal of Biometeorology*, *63*(7), 939-947. https://doi.org/10.1007/s00484-019-01706-0

Leon-Velarde, C. U., McMillan, I., Gentry, R. D., & Wilton, J. W. (1995). Models for estimating typical lactation curves in dairy cattle. *Journal of Animal Breeding and Genetics*, *112*(1-6), 333-340. https://doi.org/10.1111/j.1439-0388.1995.tb00575.x

Liseune, A., Salamone, M., Van den Poel, D., Van Ranst, B., & Hostens, M. (2020). Leveraging latent representations for milk yield prediction and interpolation using deep learning. *Computers and Electronics in Agriculture*, *175*, 105600. https://doi.org/10.1016/j.compag.2020.105600

Liseune, A., Salamone, M., Van den Poel, D., Van Ranst, B., & Hostens, M. (2021). Predicting the milk yield curve of dairy cows in the subsequent lactation period using deep learning. *Computers and Electronics in Agriculture*, *180*, 105904. https://doi.org/10.1016/j.compag.2020.105904

Lu, Y., He, X., Wen, Y., & Wang, P. S. P. (2014). A new cow identification system based on iris analysis and recognition. *International Journal of Biometrics*, *6*(1), 18-32. https://doi.org/10.1504/IJBM.2014.059639

doi:10.6342/NTU202303425

Markets and Markets. (2022). *Livestock Monitoring Market by Livestock Type (Cattle, Poultry, Swine, Equine), Application (Milk Harvesting Management, Heat Detection Monitoring, Feeding Management, Health Monitoring Management), Offering and Geography (2022-2030)*. https://www.marketsandmarkets.com/Market-Reports/livestock-monitoring-market-72634532.html

Martinez, A., Schoenig, S., Andresen, D., & Warren, S. (2006). *Ingestible Pill for Heart Rate and Core Temperature Measurement in Cattle.* 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, New York, USA. https://doi.org/10.1109/IEMBS.2006.259226

Mayo, L. M., Silvia, W. J., Ray, D. L., Jones, B. W., Stone, A. E., Tsai, I. C., Clark, J. D., Bewley, J. M., & Heersche, G. (2019). Automated estrous detection using multiple commercial precision dairy monitoring technologies in synchronized dairy cows. *Journal of Dairy Science*, *102*(3), 2645-2656. https://doi.org/https://doi.org/10.3168/jds.2018-14738

Milan, H. F. M., Maia, A. S. C., & Gebremedhin, K. G. (2016). Technical note: Device for measuring respiration rate of cattle under field conditions1. *Journal of Animal Science*, *94*(12), 5434-5438. https://doi.org/10.2527/jas.2016-0904

Ministère de l'Agriculture et de la Souveraineté alimentaire, France. (2022) Robots agricoles : où en est-on ? [Agricultural Robots: Where Are We?]. https://agriculture.gouv.fr/robots-agricoles-ou-en-est

Ministry of Agriculture, Forestry and Fishery [MAFF], Japan. (2023). *The 96th Statistical Yearbook of Ministry of Agriculture, Forestry and Fisheries.* https://www.maff.go.jp/e/data/stat/96th/index.html

Monteiro, A., Santos, S., & Gonçalves, P. (2021). Precision Agriculture for Crop and

doi:10.6342/NTU202303425

Livestock Farming—Brief Review. *Animals*, *11*(8). https://doi.org/10.3390/ani11082345

Moretti, R., Biffani, S., Chessa, S., & Bozzi, R. (2017). Heat stress effects on Holstein dairy cows' rumination. *animal*, *11*(12), 2320-2325. https://doi.org/10.1017/S1751731117001173

Murphy, M. D., O'Mahony, M. J., Shalloo, L., French, P., & Upton, J. (2014). Comparison of modelling techniques for milk-production forecasting. *Journal of Dairy Science*, *97*(6), 3352-3363. https://doi.org/10.3168/jds.2013-7451

Nabokov, V. I., Novopashin, L. A., Denyozhko, L. V., Sadov, A. A., Ziablitckaia, N. V., Volkova, S. A., & Speshilova, I. V. (2020). Applications of feed pusher robots on cattle farmings and its economic efficiency. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies 11*. https://doi.org/10.14456/ITJEMAST.2020.270

Nguyen, Q. T., Fouchereau, R., Frénod, E., Gerard, C., & Sincholle, V. (2020). Comparison of forecast models of production of dairy cows combining animal and diet parameters. *Computers and Electronics in Agriculture*, *170*, 105258. https://doi.org/10.1016/j.compag.2020.105258

Nienaber, J. A., & Hahn, G. L. (2007). Livestock production system management responses to thermal challenges. *International Journal of Biometeorology*, *52*(2), 149-157. https://doi.org/10.1007/s00484-007-0103-x

Niloofar, P., Francis, D. P., Lazarova-Molnar, S., Vulpe, A., Vochin, M.-C., Suciu, G., Balanescu, M., Anestis, V., & Bartzanas, T. (2021). Data-driven decision support in livestock farming for improved animal health, welfare and greenhouse gas emissions: Overview and challenges. *Computers and Electronics in Agriculture*, *190*, 106406. https://doi.org/10.1016/j.compag.2021.106406

doi:10.6342/NTU202303425

Nleya, S. M., & Ndlovu, S. (2021). Smart Dairy Farming Overview: Innovation, Algorithms and Challenges. In A. Choudhury, A. Biswas, T. P. Singh, & S. K. Ghosh (Eds.), *Smart Agriculture Automation Using Advanced Technologies: Data Analytics and Machine Learning, Cloud Architecture, Automation and IoT* (pp. 35-59). Springer Singapore. https://doi.org/10.1007/978-981-16-6124-2_3

Numbeo (n.d.) *Price Rankings by Country of Milk (regular), (1 liter) (Markets)*. Retreived May 25, 2023. https://www.numbeo.com/cost-of-living/country_price_rankings?itemId=8&displayCurrency=USD

Okura, F., Ikuma, S., Makihara, Y., Muramatsu, D., Nakada, K., & Yagi, Y. (2019). RGB-D video-based individual identification of dairy cows using gait and texture analyses. *Computers and Electronics in Agriculture*, *165*, 104944. https://doi.org/10.1016/j.compag.2019.104944

Olori, V. E., Brotherstone, S., Hill, W. G., & McGuirk, B. J. (1999). Fit of standard models of the lactation curve to weekly records of milk production of cows in a single herd. *Livestock Production Science*, *58*(1), 55-63. https://doi.org/10.1016/S0301-6226(98)00194-8

Organization for Economic Co-operation and Development [OECD]. & Food and Agriculture Organization of the United Nations [FAO]. (2022). *OECD-FAO Agricultural Outlook 2022-2031*. https://doi.org/10.1787/f1b0b29c-en

Pereira, P. C. (2014). Milk nutritional composition and its role in human health. *Nutrition*, *30*(6), 619-627. https://doi.org/10.1016/j.nut.2013.10.011

Peyraud, J. L., & Delagarde, R. (2013). Managing variations in dairy cow nutrient supply under grazing. *animal*, *7*(s1), 57-67. https://doi.org/10.1017/S1751731111002394

Porto, S. M. C., Arcidiacono, C., Anguzza, U., & Cascone, G. (2013). A computer

doi:10.6342/NTU202303425

vision-based system for the automatic detection of lying behaviour of dairy cows in free-stall barns. *Biosystems Engineering*, *115*(2), 184-194. https://doi.org/10.1016/j.biosystemseng.2013.03.002

Porto, S. M. C., Arcidiacono, C., Anguzza, U., & Cascone, G. (2015). The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. *Biosystems Engineering*, *133*, 46-55. https://doi.org/10.1016/j.biosystemseng.2015.02.012

Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., & Sukkarieh, S. (2021). Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation. *Computers and Electronics in Agriculture*, *185*, 106143. https://doi.org/10.1016/j.compag.2021.106143

Ratnakaran, A., Sejian, V., Jose, V., Vaswani, S., Madiajagan, B., Krishnan, G., Vakayil, B., Devi, P., Varma, G., & Bhatta, R. (2016). Behavioral Responses to Livestock Adaptation to Heat Stress Challenges. *Asian Journal of Animal Sciences*, *11*, 1-13. https://doi.org/10.3923/ajas.2017.1.13

Rhoads, M. L., Rhoads, R. P., VanBaale, M. J., Collier, R. J., Sanders, S. R., Weber, W. J., Crooker, B. A., & Baumgard, L. H. (2009). Effects of heat stress and plane of nutrition on lactating Holstein cows: I. Production, metabolism, and aspects of circulating somatotropin1. *Journal of Dairy Science*, *92*(5), 1986-1997. https://doi.org/10.3168/jds.2008-1641

Roelofs, J. B., van Eerdenburg, F. J. C. M., Soede, N. M., & Kemp, B. (2005). Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. *Theriogenology*, *64*(8), 1690-1703. https://doi.org/10.1016/j.theriogenology.2005.04.004

doi:10.6342/NTU202303425

Rossing, W., & Hogewerf, P. H. (1997). State of the art of automatic milking systems. *Computers and Electronics in Agriculture*, *17*(1), 1-17. https://doi.org/10.1016/S0168-1699(96)01229-X

Ruegg, P. L., & Reinemann, D. J. (2002). Milk quality and mastitis tests. *The Bovine Practitioner*, *36*(1), 41–54. https://doi.org/10.21423/bovine-vol36no1p41-54

Ruiz-Garcia, L., & Lunadei, L. (2011). The role of RFID in agriculture: Applications, limitations and challenges. *Computers and Electronics in Agriculture*, *79*(1), 42-50. https://doi.org/10.1016/j.compag.2011.08.010

Ruuska, S., Kajava, S., Mughal, M., Zehner, N., & Mononen, J. (2016). Validation of a pressure sensor-based system for measuring eating, rumination and drinking behaviour of dairy cattle. *Applied Animal Behaviour Science*, *174*, 19-23. https://doi.org/https://doi.org/10.1016/j.applanim.2015.11.005

Sato, S., Mizuguchi, H., Ito, K., Ikuta, K., Kimura, A., & Okada, K. (2012). Technical note: Development and testing of a radio transmission pH measurement system for continuous monitoring of ruminal pH in cows. *Preventive Veterinary Medicine*, *103*(4), 274-279. https://doi.org/10.1016/j.prevetmed.2011.09.004

Schaefer, A. L., Cook, N. J., Bench, C., Chabot, J. B., Colyn, J., Liu, T., Okine, E. K., Stewart, M., & Webster, J. R. (2012). The non-invasive and automated detection of bovine respiratory disease onset in receiver calves using infrared thermography. *Research in Veterinary Science*, *93*(2), 928-935. https://doi.org/10.1016/j.rvsc.2011.09.021

Schaeffer, L. R., & Jamrozik, J. (1996). Multiple-Trait Prediction of Lactation Yields for Dairy Cows. *Journal of Dairy Science*, *79*(11), 2044-2055. https://doi.org/10.3168/jds.S0022-0302(96)76578-5

Schwartzkopf-Genswein, K. S., Stookey, J. M., & Welford, R. (1997). Behavior of

doi:10.6342/NTU202303425

cattle during hot-iron and freeze branding and the effects on subsequent handling ease1. *Journal of Animal Science*, *75*(8), 2064-2072. https://doi.org/10.2527/1997.7582064x

Seegers, H., Fourichon, C., & Beaudeau, F. (2003). Production effects related to mastitis and mastitis economics in dairy cattle herds. *Veterinary Research*, *34*(5), 475-491. https://doi.org/10.1051/vetres:2003027

Sharma, A. K., Sharma, R. K., & Kasana, H. S. (2006). Empirical comparisons of feed-forward connectionist and conventional regression models for prediction of first lactation 305-day milk yield in Karan Fries dairy cows. *Neural Computing & Applications*, *15*(3), 359-365. https://doi.org/10.1007/s00521-006-0037-y

Sharma, A. K., Sharma, R. K., & Kasana, H. S. (2007). Prediction of first lactation 305-day milk yield in Karan Fries dairy cattle using ANN modeling. *Applied Soft Computing*, *7*(3), 1112-1120. https://doi.org/10.1016/j.asoc.2006.07.002

Sharma, B., & Koundal, D. (2018). Cattle health monitoring system using wireless sensor network: a survey from innovation perspective. *IET Wireless Sensor Systems*, *8*(4), 143-151. https://doi.org/10.1049/iet-wss.2017.0060

Šístkova, M., Pšenka, M., Kaplan, V., Potěšil, J., & Černín, J. (2015). The effect of individual components of total mixed ration (TMR) on precision dosing to mixer feeder wagons. *Journal of Microbiology, Biotechnology and Food Sciences*, *5*(1), 60-63.

Smith, K., Martinez, A., Craddolph, R., Erickson, H., Andresen, D., & Warren, S. (2006). *An Integrated Cattle Health Monitoring System.* 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, New York, USA. https://doi.org/10.1109/IEMBS.2006.259693

Smith, L. P. (1968). Forecasting annual milk yields. *Agricultural Meteorology*, *5*(3),

doi:10.6342/NTU202303425

209-214. https://doi.org/10.1016/0002-1571(68)90004-6

Stankovski, S., Ostojic, G., Senk, I., Rakic-Skokovic, M., Trivunovic, S., & Kucevic, D. (2012). Dairy cow monitoring by RFID. *Scientia Agricola*, *69*(1), 75-80. https://doi.org/10.1590/S0103-90162012000100011

Strutzke, S., Fiske, D., Hoffmann, G., Ammon, C., Heuwieser, W., & Amon, T. (2019). Technical note: Development of a noninvasive respiration rate sensor for cattle. *Journal of Dairy Science*, *102*(1), 690-695. https://doi.org/10.3168/jds.2018-14999

Sun, S., Yang, S., & Zhao, L. (2013). Noncooperative bovine iris recognition via SIFT. *Neurocomputing*, *120*, 310-317. https://doi.org/10.1016/j.neucom.2012.08.068

Tran, D. N., Nguyen, T. N., Khanh, P. C. P., & Tran, D. T. (2022). An IoT-Based Design Using Accelerometers in Animal Behavior Recognition Systems. *IEEE Sensors Journal*, *22*(18), 17515-17528. https://doi.org/10.1109/JSEN.2021.3051194

Tuan, S.-A., Rustia, D. J. A., Hsu, J.-T., & Lin, T.-T. (2022). Frequency modulated continuous wave radar-based system for monitoring dairy cow respiration rate. *Computers and Electronics in Agriculture*, *196*, 106913. https://doi.org/https://doi.org/10.1016/j.compag.2022.106913

Ungar, E. D., Henkin, Z., Gutman, M., Dolev, A., Genizi, A., & Ganskopp, D. (2005). Inference of Animal Activity From GPS Collar Data on Free-Ranging Cattle. *Rangeland Ecology & Management*, *58*(3), 256-266. https://doi.org/10.2111/1551-5028(2005)58[256:IOAAFG]2.0.CO;2

U.S. Department of Agriculture [USDA]. (2022). Taiwan: Dairy and Products Annual. https://www.fas.usda.gov/data/taiwan-dairy-and-products-annual-3

Vitali, A., Segnalini, M., Bertocchi, L., Bernabucci, U., Nardone, A., & Lacetera, N. (2009). Seasonal pattern of mortality and relationships between mortality and

doi:10.6342/NTU202303425

temperature-humidity index in dairy cows. *Journal of Dairy Science*, *92*(8), 3781-3790. https://doi.org/10.3168/jds.2009-2127

Voulodimos, A. S., Patrikakis, C. Z., Sideridis, A. B., Ntafis, V. A., & Xylouri, E. M. (2010). A complete farm management system based on animal identification using RFID technology. *Computers and Electronics in Agriculture*, *70*(2), 380-388. https://doi.org/10.1016/j.compag.2009.07.009

Wallace, T. C., Bailey, R. L., Lappe, J., O'Brien, K. O., Wang, D. D., Sahni, S., & Weaver, C. M. (2021). Dairy intake and bone health across the lifespan: a systematic review and expert narrative. *Critical Reviews in Food Science and Nutrition*, *61*(21), 3661-3707. https://doi.org/10.1080/10408398.2020.1810624

Wang, H., Qin, J., Hou, Q., & Gong, S. (2020). Cattle Face Recognition Method Based on Parameter Transfer and Deep Learning. *Journal of Physics: Conference Series*, *1453*(1), 012054. https://doi.org/10.1088/1742-6596/1453/1/012054

Wang, T., Xu, X., Wang, C., Li, Z., & Li, D. (2021). From Smart Farming towards Unmanned Farms: A New Mode of Agricultural Production. *Agriculture*, *11*(2). https://doi.org/10.3390/agriculture11020145

Warnick, L. D., Janssen, D., Guard, C. L., & Gröhn, Y. T. (2001). The Effect of Lameness on Milk Production in Dairy Cows. *Journal of Dairy Science*, *84*(9), 1988-1997. https://doi.org/10.3168/jds.S0022-0302(01)74642-5

Weng, Z., Meng, F., Liu, S., Zhang, Y., Zheng, Z., & Gong, C. (2022). Cattle face recognition based on a Two-Branch convolutional neural network. *Computers and Electronics in Agriculture*, *196*, 106871. https://doi.org/10.1016/j.compag.2022.106871

West, J. W. (2003). Effects of Heat-Stress on Production in Dairy Cattle. *Journal of Dairy Science*, *86*(6), 2131-2144. https://doi.org/10.3168/jds.S0022-

doi:10.6342/NTU202303425

0302(03)73803-X

Wood, P. D. P. (1967). Algebraic Model of the Lactation Curve in Cattle. *Nature*, *216*(5111), 164-165. https://doi.org/10.1038/216164a0

Wu, D., Wang, Y., Han, M., Song, L., Shang, Y., Zhang, X., & Song, H. (2021). Using a CNN-LSTM for basic behaviors detection of a single dairy cow in a complex environment. *Computers and Electronics in Agriculture*, *182*, 106016. https://doi.org/10.1016/j.compag.2021.106016

Xia, L., Chunxia, S., & Ming, T. (2020). *Design and Implementation of Intelligent Ear Tag for Dairy Cows in Farms* Proceedings of the 2020 9th International Conference on Software and Computer Applications, Langkawi, Malaysia. https://doi.org/10.1145/3384544.3384574

Yao, L., Hu, Z., Liu, C., Liu, H., Kuang, Y., & Gao, Y. (2019). *Cow face detection and recognition based on automatic feature extraction algorithm* Proceedings of the ACM Turing Celebration Conference - China, Chengdu, China. https://doi.org/10.1145/3321408.3322628

Zehner, N., Niederhauser, J. J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Haeussermann, A., & Schick, M. (2016). *Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows.* Proceedings of the International Conference of Agricultural Engineering -CIGR-AgEng 2012: Agriculture and Engineering for a Healthier Life, Valencia, Spain.

Zhang, W., Yang, K., Yu, N., Cheng, T., & Liu, J. (2020, 6-9 Dec. 2020). *Daily milk yield prediction of dairy cows based on the GA-LSTM algorithm.* 2020 15th IEEE International Conference on Signal Processing (ICSP), Beijing, China. https://doi.org/10.1109/ICSP48669.2020.9320926.

doi:10.6342/NTU202303425

酪農 PLUS+. (2020). *日本における搾乳ロボットの普及と地域による利用特性* [Diffusion of Milking Robots in Japan and Regional Characteristics of Their Utilization]. https://rp.rakuno.ac.jp/archives/feature/3377.html

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Appendix A

Cattle milk production in 2020 in France, Japan, and Taiwan

		Taiwan	Japan	France
Population	million persons	23.8	125.2	64.5
Land area	sq. km	32,260	364,485	549,970
Raw cattle milk production	1000 t	437	7,438	25,235
Number of dairy cattle (for milking)	1000 heads	63	839	3,406
Average yield	kg/cow	6937	8866	7409
Number of dairy farms	farms	560	14,400	50,289
Average number of cows per farm	heads	113	58	68
per Capita consumption	kg	21.65	31.6	198.5
Import	1000 t	171	369	2984
Export	1000 t	1	10	5506
Milk Price (2023.5.25)	USD/liter	3.05	1.41	1.14

Note. Original data were obtained FAOSTAT (FAO, n.d.), The World Factbook (Central Intelligence Agency [CIA], n.d.), Council of Agriculture (2021), MAFF (2023), Agreste (2022), Eurostat (n.d.), and Numbeo (n.d.).

References not in the list above

Central Intelligence Agency [CIA]. (n.d.). *The World Factbook*.

https://www.cia.gov/the-world-factbook/

Eurostat. (n.d.). *EU-27 estimated agricultural balance sheets*.

https://datam.jrc.ec.europa.eu/datam/mashup/EU_ESTIMATED_AGRICULTURAL_BALANCE_SHEETS/index.html

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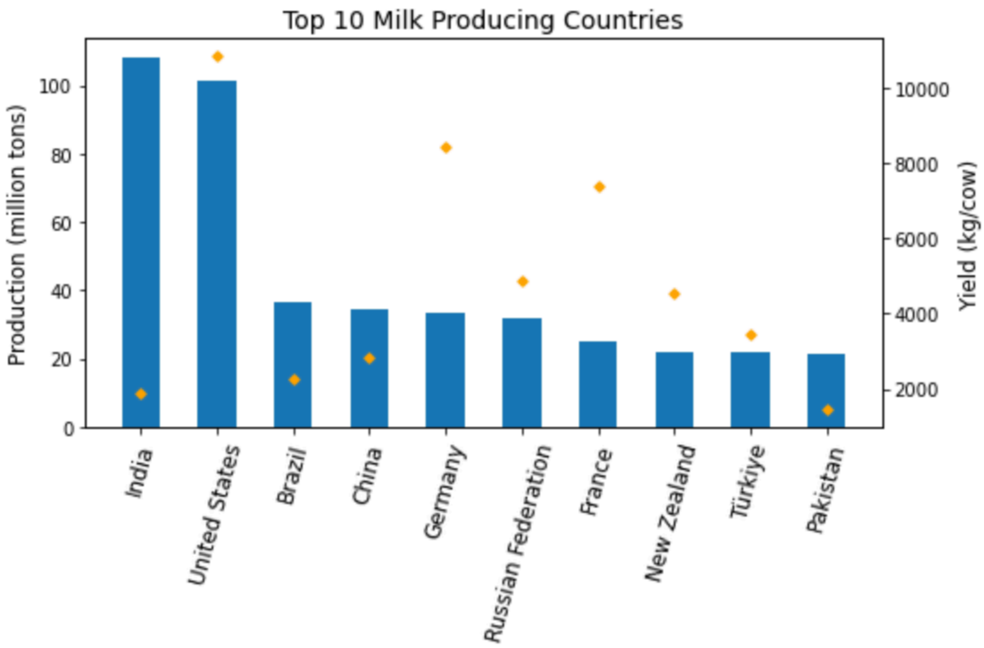
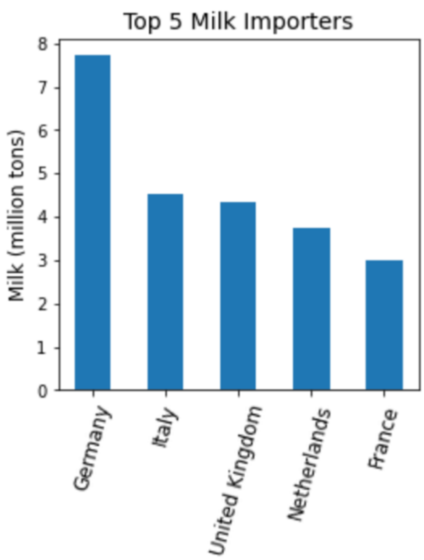
Appendix B

Top milk producing, importing, and exporting countries in 2020

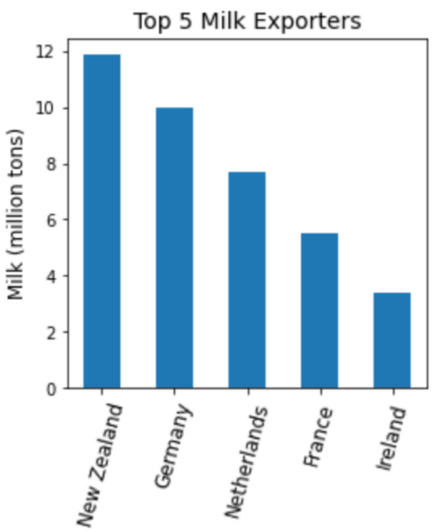
a



b



c



Note. (a) Top 10 milk producing countries in 2020. Blue bars are the milk productions (left), while orange diamonds represent the yield of each cow (right). Original data were obtained from Production (Raw milk of cattle), FAOSTAT (FAO, n.d.). (b) Top 5 milk importers in 2020. (c) Top 5 milk exporters in 2020. Original data were obtained from Food Balance Sheets (Milk - Excluding Butter), FAOSTAT (FAO, n.d.).

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Appendix C

Results of each model

		SVR	RF	XGB
F1	Correlation Coefficient	0.7013	0.6746	0.7071
	RMSE	6.2965	6.5527	6.2324
	Accuracy	74.86%	74.47%	75.35%
F2	Correlation Coefficient	0.7269	0.7639	0.7860
	RMSE	6.0660	5.6810	5.4429
	Accuracy	76.07%	78.53%	79.46%
F3	Correlation Coefficient	0.7287	0.7724	0.7869
	RMSE	6.0483	5.5907	5.4323
	Accuracy	76.20%	78.78%	79.57%
F4	Correlation Coefficient	0.7192	0.7721	0.7853
	RMSE	6.1363	5.5983	5.4529
	Accuracy	75.69%	78.79%	79.48%
F5	Correlation Coefficient	0.7200	0.7646	0.7764
	RMSE	6.1298	5.6732	5.5500
	Accuracy	75.62%	78.38%	78.98%
F5 (tuned)	Correlation Coefficient	0.7441	0.7732	0.7991
	RMSE	5.9378	5.5866	5.2937
	Accuracy	**77.18%**	**78.64%**	**80.21%**
Prediction of Data in 2018	Correlation Coefficient	0.6898	0.7194	0.7208
	RMSE	6.3057	5.8317	5.8607
	Accuracy	**74.68%**	**75.95%**	**76.33%**

Note. RMSE: root mean squared error.

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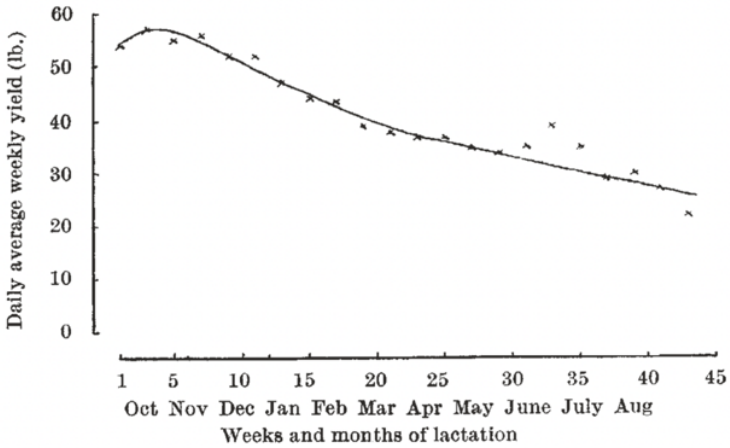
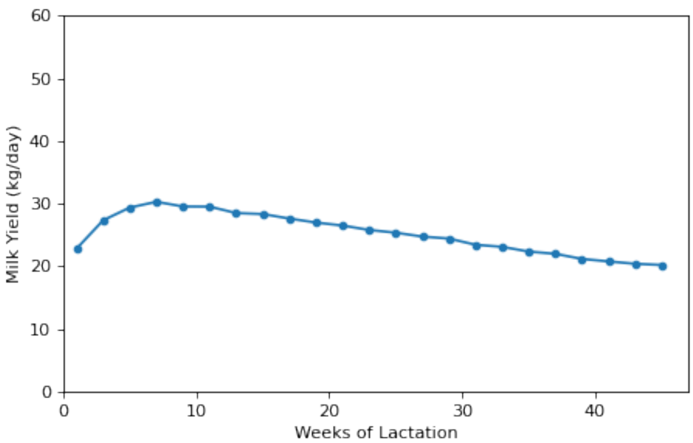
Appendix D

Comparison of the lactation curves between Wood (1967) and this study

a



b



Note. (a) The lactation curve proposed by (Wood, 1967): A regression curve fitted to a single lactation. (b) The mean curve of milk yield by weeks of lactation, under same time zone as (a).

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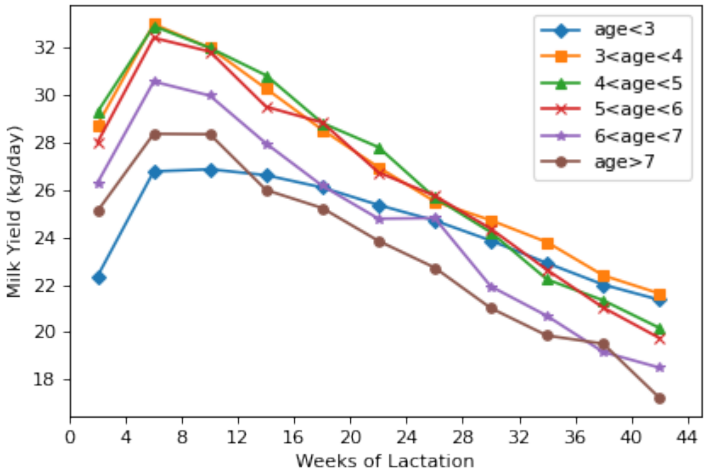
Appendix E

Lactation curves at different ages



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