

Machine Learning based Product Quantity and Quality Prediction in Food Production

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In food production, numerous factors significantly influence both the growth and quality of products. Predicting product quality and quantity in an early stage and precise way is particularly difficult. For accurate order planning, reducing waste, and ensuring customer satisfaction, production planners need to know the provided product quality and quantity from the suppliers in a precise way. To address this need and support planners in their daily decision-making processes, an approach has been created that involves the development and application of machine learning models aimed at initially predicting product quantity and subsequently product quality in two distinct phases. The developed machine learning pipeline focuses specifically on the case study of raspberry production. By utilizing production and field data, alongside publicly available weather data and synthetic datasets, various machine learning models were tested and validated.

Keywords— Machine learning, predictive quality, predictive quantity, food production

I. INTRODUCTION

A. Initial Situation

The food packaging industry plays a crucial role in the global distribution of food products, ensuring adherence to established quality standards [1, 2]. This sector is continually subjected to stringent regulatory pressures regarding food safety, necessitating comprehensive oversight and effective quality control measures [2]. Traditional quality assurance methods in the food packaging industry, which predominantly rely on regular manual inspections, are time consuming and create the need for more efficient and innovative strategies [3].

The emergence of Machine learning (ML) technologies offers opportunities for optimizing quality control processes [4, 5]. Automated quality assessments, facilitated by advanced vision systems, historical data analytics, and sensor integrations, have the potential to enhance operational efficiency [6, 7]. By employing algorithms designed to predict food quality based on historical data, organizations could reduce the time allocated to quality checks and improve

production planning [6–8]. Additionally, accurate demand forecasting and resource allocation are essential to mitigate the risks of overproduction and shortages, thereby ensuring product freshness and minimizing waste. These operational considerations underscore the need for streamlined processes and improved decision-making, achievable through the application of data-driven models, which provide suitable information based on data analysis and can therefore predict, for example, the number of mature food products [9–11].

Recent advancements in machine learning, in conjunction with Industry 4.0 technologies such as the Internet of Things (IoT), address these challenges by automating quality control and enhancing supply chain resilience [3, 11]. IoT devices facilitate the collection of real-time data on various production variables. When integrated with data analytics, this information provides a comprehensive dataset for analysis by machine learning algorithms [12]. This integration not only allows for the automation of quality checks but also improves the precision of traceability and forecasting systems, thereby enhancing operational efficiency and food safety standards [13, 14]. In comparison to that, the industry is often facing problems by getting data in an early stage of the food products lifecycle to improve production handling and scheduling processes. Especially the lack of standardized data provision from the supplier of the raw products is quite challenging for the food packing industry [15, 16].

Despite these technological advancements, a notable research gap exists in the application of predictive modelling, particularly concerning the early-stage prediction of quality and quantity for various food products. Existing literature often focuses on general food quality control or employs technologies such as spectroscopy to assess quality, with few studies integrating operational and supplier data to anticipate quality variations in food products at an early stage [17–20]. This identified gap highlights the need for further research and development in the application of predictive analytics to enhance quality assurance processes within the food packaging sector.

In the present work, the aim is to close this research gap by developing an ML pipeline for the early prediction of the raspberry product quality and quantity in the agriculture industry to support the production planner in their daily scheduling processes. The solution provides specific forecast values for the expected quantity and quality classes that will be provided by different suppliers in the coming days. Based on the rapidly changing quality status of raspberries, these predictions can provide gainful decision support for the batch and order handling of production planners. Using various data sources from production, the field and the weather, an ML pipeline is to be developed. By using data analytics and sophisticated ML techniques, the aim is to increase operational efficiency of batch and order scheduling and significantly reduce waste to ultimately create a more sustainable production environment.

The paper at hand is structured in the following way. First a scientific literature survey will be presented to provide an overview of the existing approaches for predicting the quality and quantity of products in the agriculture sector and to show the identified gaps. Additional to that, important impact factors of the raspberry production which will be crucial for the developed use case, were identified. After that the research approach including the selected raspberry use case and the defined boundary conditions is shown. Moreover, the developed ML pipeline is comprehensively described. Furthermore, to validate the ML pipeline, the achieved results for the product quality prediction will be shown after that. Finally, a brief summary of the research results obtained is presented.

II. RELATION TO EXISTING THEORIES AND WORK

A. State of the art

In the state-of-the-art chapter existing approaches were identified and differentiation and gaps between them and the developed solution in this paper are given.

D. Elavarasan et al. [21], A. Sharma et al. [22] and E. Elbasi et al. [23] explored the usage of various analytical models like Decision Trees, Random Forests, Support Vector Machines, Bayesian Networks, and Artificial Neural Networks to analyze environmental impacts which are significantly relevant for the growth, availability and quality of the different food products. Therefore, the developed ML models were feed with parameters like pH-value, soil type, and quality, weather pattern, temperature, rainfall and further parameters. These presented approaches have shown the potential of the usage of different ML algorithm for gaining for the farmer and production planer useful information to increase the productivity in agriculture food sector. Nevertheless, it is shown that the individual models are still limited in their field of application and also have very limited ability to deal with the complex interrelationships of real-life scenarios. [21–23]

Crane-Droesch et al. [24] focused on predicting crop yields, specifically corn in the U.S. Midwest, to assess the impact of climate change on the yields in agriculture food sector. They used a semiparametric neural network (SNN), combining machine learning with traditional regression models to improve prediction accuracy. This approach accounts for complex, nonlinear relationships between climate and crop yield while incorporating prior knowledge of the field. It showed better predictive performance than both traditional statistical methods and nonparametric neural

networks. By merging a regression model with deep learning, the SNN increases accuracy and efficiency in forecasting yields. However, the model is limited to corn and a specific region, which affects its broader applicability. Unlike traditional models, the SNN projects less severe yield declines in warmer climates. It also emphasizes the importance of factors like the timing of heat and moisture for accurate yield predictions. [24]

A further study, published by Ansarifard et al. [25], presents an Interaction Regression Model (IRM) for predicting crop yields of corn and soybean in the U.S. Midwest. The model aims to achieve both, high prediction accuracy and explainability by combining optimization techniques, ML, and agronomic knowledge. It identifies the key factors affecting crop yield, such as weather, soil, and management, along with their interactions. The machine learning technique combines combinatorial optimization and multiple linear regression, allowing it to identify important features and interactions that influence yield. Although the model significantly improves prediction accuracy compared to other methods, it still faces challenges in handling complex interactions and large datasets. Additionally, it is limited to corn and the identified and used parameter are difficult to transfer to the area of raspberry production. [25]

Nosratabadi et al. [26] focus in their study on predicting food production at a macro level in Iran, with an emphasis on agricultural and livestock production. The research specifically tackles the need for accurate predictions of food production, which are essential for planning domestic production, imports, and workforce management in the agricultural sector. The research is at the prototype stage, where two machine learning models, the Adaptive Network-Based Fuzzy Inference System (ANFIS) and the Multilayer Perceptron (MLP), are compared for their predictive performance. Among these, the ANFIS model, demonstrated superior accuracy in predicting agricultural and livestock production trends based on historical time-series data. This approach takes an overarching view of agricultural production and livestock farming and does not focus on specific products. For this reason, other parameters are analyzed here than those for the product quality forecasts of a specific product like raspberries. The findings are specific to climate and production conditions of Iran, meaning that the results may not directly apply to other countries or regions like Europe with different agricultural and economic conditions. [26]

Another approach published by Niedbala et al. [27], presented a high-accuracy model for predicting blueberry yields using machine learning techniques. The approach is built upon the integration of diverse datasets, including agronomic, climatic, soil, and satellite-imaging vegetation data collected over the years 2016–2021. By incorporating such a wide range of data, the model aims to achieve accurate yield predictions that can assist in improved decision-making processes for blueberry farms, including harvest planning, storage allocation, and resource management. Different ML models, including advanced methods like Extreme Gradient Boosting (XGBoost), Random Forest were tested. This research is currently focusing to the specific blueberry varieties and geographic conditions of southeastern Poland. For the model to be applicable in other regions with different climatic conditions, additional research and adaptations are necessary. Moreover the raspberry production has further

specific impact parameters which are not considered in this approach. [27]

Borrero et al. [28] present a study about berries where a hybrid model was designed to improve the accuracy of short-term berry yield predictions. It combines ARIMA (Autoregressive Integrated Moving Average) with a Kalman filter, along with machine learning techniques like Support Vector Regression (SVR) and Nonlinear Autoregressive (NAR) neural networks. The approach focuses on predicting weekly berry yields to assist farmers in planning production, optimizing resources, and increasing efficiency. Unlike the goal of including additional data such as climate or imagery, this model relies solely on historical yield data and is not specified on raspberries and parameters which impact the growth of berries. [28]

Lee et al. [29] have published an ML use case involving the accurate prediction of harvest time for soft fruits, a critical aspect due to the perishability and time sensitivity of these crops. The primary objective is to enhance the accuracy of harvest timing predictions, enabling growers to optimize labor and harvesting schedules. The study employs a gradient descent algorithm to optimize the parameters of a logistic growth curve, modeling fruit yields over time. Environmental factors, such as relative humidity and air temperature, are also integrated into the model to improve its predictive capability. It has been successfully tested on strawberries, demonstrating its potential. However, the framework is not yet scalable to other fruits and depends on the accuracy of environmental sensors and the quality of input data. [29]

All these approaches and research leverage a diverse range of machine learning algorithms, each tailored to address specific challenges within the field. However, the different parameters and individual model set ups often limits their applicability to other product use cases like raspberries. Moreover, they depend on varying datasets with individual data quality, which is highly impacting the model performance as well. The examples highlighted shows different limitations and challenges which were identified in presented use cases and particularly in applications involving raspberries production underscoring the need for further research and solution approaches in the case of raspberries. This is particularly due to the fact that raspberry quality depends on many factors and a loss of quality can occur if handled incorrectly in the field or in production.

B. Challenges and gaps, objectives

Based on the presented existing approaches it is shown that ML is already introduced in the agriculture sector and also first approaches for predicting product quality are done. Moreover, the range of applications is large and the use cases very individual and specific. Nevertheless, there are some challenges and gaps that have been identified in the existing approaches.

Lack of data: A good data basis with high data quality is crucial for the performance of the models used. Due to the inclusion of various data sources and the complexity of the various influences on the product, it is often necessary to record data completely and extensively over several years. Especially when several stakeholders are involved, data exchange is a major challenge in this sector in addition to data collection. Not every field is equipped with sufficient sensors and manual data collection is prone to errors. a [25, 26, 28, 29]

Lack of technology acceptance: Conservative behavior makes it difficult to use and integrate new technologies such as ML to support production in the agricultural sector. The use of ML is also made more difficult by the fact that improvements are often not guaranteed and the return on invest cannot be precisely quantified in most cases. [26, 30]

Lack of integrated approaches: A few approaches have demonstrated the potential of taking weather data into account in addition to production and field data. Building on this, a holistic view of these factors from historical data as well as current and future data, which have a significant influence on product quality, can lead to improvements in the early detection of products in the agricultural sector. [30, 31]

C. Impact parameter for raspberry production

For the solution development different impact parameter where identified, which are highly influencing the raspberry production. Factors such as temperature, sunlight, water and humidity, soil conditions, and post-harvesting handling directly influence fruit growth, quality, and yield. Effective management of these parameters is essential for ensuring high-quality raspberries and meeting market demands. [32, 33]

Temperature: Raspberries thrive within specific temperature ranges, as deviations, whether extreme heat or cold, can affect plant health, fruit quality, and ripening. High temperatures during harvest may lead to overripening and reduced marketability, while cooler temperatures can slow ripening but increase fungal disease risks when paired with high humidity [34–36].

Sunlight: Adequate sunlight is vital for photosynthesis and fruit quality, but excessive direct sunlight can cause sunscald, damaging the fruit and effecting the marketability. Strategies like shade cloths can help regulate exposure, maintaining optimal growth conditions [34–37].

Water and Humidity: Consistent moisture levels are critical for raspberries, with excessive moisture fostering fungal diseases (e.g., *Botrytis cinerea*) and insufficient water stressing the plants. Drip irrigation and high tunnels effectively address these challenges, ensuring balanced moisture levels [35, 38–41].

Soil and Nutrient Conditions: Raspberries grow best in well-drained, slightly acidic soils (pH 5.5–6.5). Regular soil testing, organic matter additions, and nutrient management are crucial for maintaining soil fertility and supporting plant productivity during critical growth phases to assure fruit quality and marketability [42–44].

Post-Harvest Handling: Rapid cooling and controlled atmosphere storage with elevated CO₂ and reduced O₂ levels help preserve fruit quality post-harvest. This approach minimizes respiration, ethylene production, and pathogen growth, extending the shelf life of raspberries, which is crucial for ensuring demand for raspberry production [37].

Adaptation to Climatic Extremes: Heatwaves and cold spells necessitate adaptive strategies like shade cloths or frost protection to mitigate risks during harvest. Monitoring weather forecasts and employing timely interventions are essential to protect yields [45].

Altitude: A higher altitude positively impacts raspberry cultivation by offering cooler temperatures and increased sunlight exposure, which can enhance the mineral and nutrient

content of the fruit. While the growing season may be shorter, the unique conditions at higher altitudes result in raspberries that can be processed and preserved, offering both nutritional benefits and extended shelf life for consumers. [46].

III. RESEARCH APPROACH

A. Use Case Description

The focus of the paper is on the development of a ML pipeline for prediction of product quantity and quality of raspberries which will be provided by suppliers to food packaging companies. By handling and extracting this information, the food packaging companies can calculate more precisely the quantity and quality value of products which will be delivered in the next days and weeks. The quantity is measured in total kilograms per supplier, location and variety. Moreover, the product quality is assessed in 5 different types which were defined by the packaging company. Type 1 represents the best product quality and type 4 represents a low quality which still can be used for example for juice production. Only the quality type 5 cannot be used anymore and represent waste.

The developed ML pipeline should support the production planner from a packaging company in his daily work of scheduling deliveries and orders by offering data driven decision making. This approach can increase operational efficiency and reduce waste in the food production process and ensures quality assurance by utilizing data analytics and machine learning techniques.

The general procedure of the ML pipeline development will be described below and is shown in Fig.1.

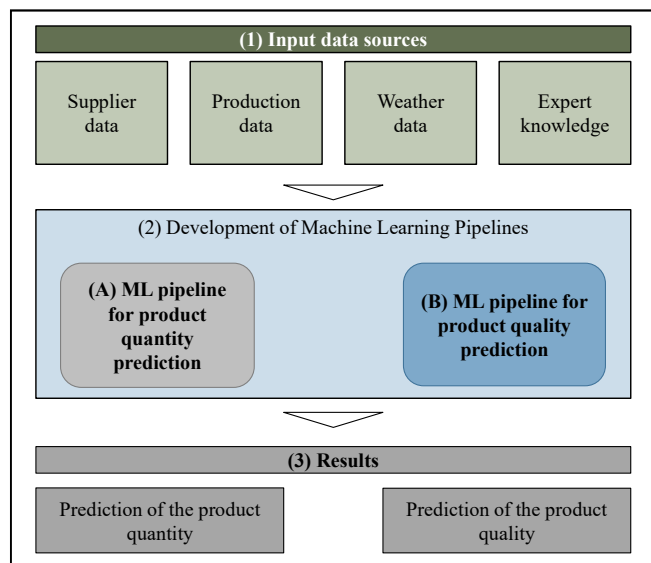


Fig. 2. Concept of the ML based product quality and quantity prediction solution

For the selected raspberry use case different data sources (1) like production data, field data, weather data and synthetic data are used as input data for the ML pipeline. The development of the ML pipeline (2) can be divided into two main parts. The first part (A) focuses on the development of a ML model to predict the raspberry product quantity which will be provided by the supplier to the packaging company, by using various data collection and preparation methods to ensure high data quality. Therefore, different models for predicting product quantity will be trained and tested and the

model with the best performance will be identified. In the second part (B) of the ML pipeline, the prediction results of the first model and the already processed data set will be used and supplemented by further processing steps to fine tune on the product quality prediction. Various models for classifying product quality then will be tested and the best model will be identified. As a result (3), the production planner is given the expected quantity of raspberries for the next 14 days for each supplier, as well as the respective quantity per quality class. This should enable more precise order planning and ensure better customer satisfaction.

B. Development of the ML pipeline

The developed ML pipeline was conceptualized based on the CRISP-DM methodology [47], which was common procedure for data science projects and is shown in Fig. 2. This methodology supports the preparation of datasets and the development of ML pipelines, extending to the evaluation of results and deployment. Using this methodology, a process for developing the ML pipeline was outlined, which is divided into the two previously mentioned phases for predicting product quantity (A) and product quality (B). Both phases are using the defined 5 steps for the pipeline development from step 1 data acquisition, orchestration and quality check to step 5 model evaluation. After following these 5 steps in phase A for the development of the pipeline for product quantity prediction, phase B is started. This phase includes roughly similar 5 steps which are used for the development of the ML pipeline for product quality prediction. The individual steps of the ML pipeline will be described in more detail below:

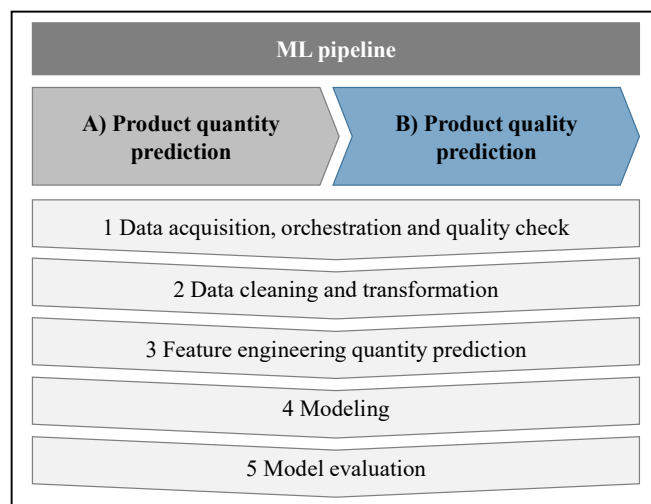


Fig. 1. Overview ML pipeline

1 Data acquisition, orchestration and quality check

As already mentioned briefly for the selected use case different data sources like production data, field data, API weather data and synthetic data are used. The production and field data contains various details such as the fruit species, fruit variety, agricultural and geographical metrics such as planting density, geographical location, and altitude at which the plants are grown, as well as harvest details. The provided dataset contains data from January 2022 to May 2024.

Furthermore, for adding specific weather information the open API Open-Meteo [48] was used to acquire data like temperature, daylight duration, and wind speed. These parameters are used to improve the accuracy of the model

prediction by including important parameter that influencing the raspberry cultivation.

In addition, a mixed synthetic dataset was generated which includes data from the years 2016 to 2021, to increase the number of data points and provide a more variable dataset for the later model training and testing. The dataset consists of the real production and field data from the data set 2022 - 2024 and were slightly adjusted using noise filters for synthetic enrichment to adapt the datapoint values of the dataset. After that, the generated synthetic dataset was obtained with data from real weather data via the API already presented. This dataset is used to improve the model robustness with additional data points. The data sets were validated separately and combined in the later model pipeline.

The provided production and field data include information about three different raspberry variants (variant 040, 082, and 121). For the variants, there are different peak seasons throughout the year, which were averaged over the recorded years of the dataset. The results also depend on various growth conditions in the fields and the individual variants themselves. An overview of the quantities of raspberries provided by the suppliers, divided into the individual variants for each month, is presented and can be seen in Fig. 3. The results are an average value for the 3 years in which data is available per month. In the figure the different peak phase of the 3 varieties 040, 082 and 121 are displayed.

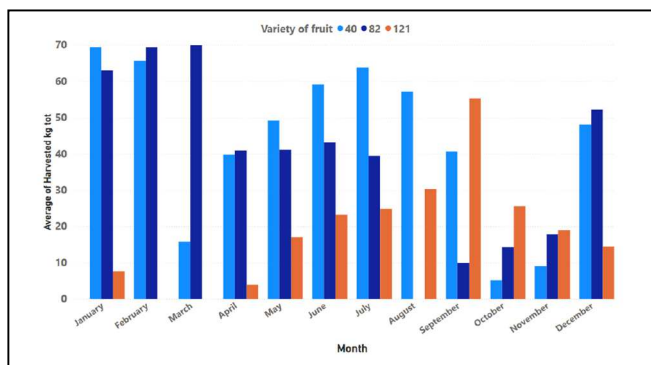


Fig. 3. Yearly overview of harvested raspberries in kg per month depending on the variety (Average of the years 2022-2024)

Moreover, the results of the individual variants from Fig. 3 were further divided into the individual quality classes in Fig. 4. It is noticeable that the suppliers provide in the most cases a high proportion of raspberries from the highest quality type.

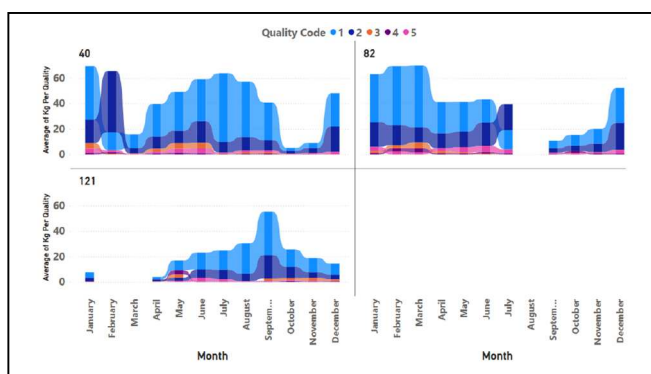


Fig. 4. Yearly overview of harvested raspberries in kg per month depending on the variety and quality classes (Average of the years 2022-2024)

Due to the different sources with different time stamps, it is important and necessary for the subsequent model development to synchronize this data so that the model can clearly assign defined events in the data set.

2 Data cleaning and transformation

As part of the data cleaning and transformation process, different steps were done. Outliers were identified and removed by applying the Z-score method to detect data points that significantly deviate from the average distribution. Subsequently, rounding methods were applied to the numerical columns in the data set to enhance consistency and the model performance. Additionally, missing values were handled by implementing techniques such as imputation or deletion based on the context of the data.

3 Feature engineering

In the feature engineering phase, additional features were generated from the existing data set to improve model performance and robustness. For the development of the product quantity prediction models, features like harvesting period, peak production status or altitude and location classes were defined. Moreover, additional features for product quality prediction were generated in phase 2, as the prediction is based on a weekly forecast. The generated features include information about the product quality status from the previous week, the product peaks per variety altitude and location.

4 Modelling

Before the modeling phase, the various datasets were divided into train test splits. After that, the different models are trained and tested on the different datasets. A wide variety of predictive models are used to determine the most effective techniques for forecasting quality and quantity metrics. The selected models consist of XGBoost, AdaBoost, Random Forest Regressor, and AdaBoost enhanced with Optuna optimization. For finetuning of the model and increasing the model performance different common hyperparameter methods like Bayesian Optimization, Optuna, Grid Search and Random Search CV were used. Libraries such as sklearn, pandas or matplotlib as well as frameworks such as tensorflow and keras were used.

5 Evaluation

To evaluate the performance of the ML-Pipeline and especially the used models, k-fold cross-validation was used, which ensures the generalizability of the model. Each model was trained and evaluated on different subsets of the dataset. To assess the performance of the model, R²-score and Root Mean Square Error (RMSE) were used as evaluation metrics. The R²-score indicates how well the model can represent the variability of the original data. Values close to 1 show that the model can represent the variability of the original data very well, while values approaching 0 indicate that the model does not make good predictions. Furthermore, RMSE serves as a metric to indicate the accuracy of the model and the predicted results. It compares the square root of the average of the squared deviations between the predicted and original values. Low RMSE values indicate good prediction accuracy. [49, 50]

IV. FINDINGS (RESULTS)

A. Results

The results for predicting product quantity (A) and product quality (B) are presented below.

1) Product quantity prediction (A)

To predict precisely the delivered quantity of raspberries in kilograms different ML pipelines were tested to identify the best performing set up (Table 1).

TABLE I. RESULTS OF THE DIFFERENT ML PIPELINES FOR PRODUCT QUANTITY PREDICTION

ID	Dataset ID	Total data count	Feature Set	Training Model	Test RMSE	Test R ²	Training RMSE	Training R ²
01	DS001	194.460	A	XGBoost Regressor	29.85440	0.5850	29.180	0.6035
02	DS001	194.460	A	XGBoost Regressor + Bayesian	28.638	0.6181	26.96	0.661416
03	DS011	191.815	C	AdaBoost Regressor	20.140	0.8113	19.417	0.8264
04	DS011	191.815	C	AdaBoost Regressor + Optuna	19.56	0.8219	19.033	0.8332
05	DS012	191.670	C	AdaBoost Regressor	23.56	0.7410	22.677	0.7633
06	DS012	191.670	C	AdaBoost Regressor + Optuna	19.6963	0.8190	19.14	0.8312
07	DS013	577.945	C	XGBoost Regressor	30.03	0.5786	29.54	0.5911
08	DS013	577.945	C	XGBoost Regressor + Bayesian	24.04	0.7299	22.766	0.7589
09	DS002	18.625	B	RandomForest Regressor	16.545	0.8025	6.2571	0.9714
10	DS002	18.625	B	XGBoost Regressor + Optuna	16.37026	0.81119	6.3537	0.970301

ID01 and ID02 (DS001): Covers data from the years 2022 to 2024 with a total of 194,460 data points. This dataset consists exclusively of original data. The Feature set A is used for building the model. The models underperformed on the test set compared to the training set, indicating potential issues with the model's ability to generalize across new, unseen data. This may be due to limitations in the feature set and the complexity of the model. The R²-score of 0.5850 for the test set shows significant amount of variability that is not being captured. For ID02, the same model was trained with Bayesian optimizer, which provides only small effects on the achieved test results of R²-Score of 0.6181.

ID03 and ID04 (DS011) and ID05 and ID06 (DS012): In ID03 and ID6 a mixed synthetic dataset was used, which covers the period from 2016 to 2018 with 191,815 entries. For this dataset, the AdaBoost regressor shows the best results compared to the other selected models. Initially, this model achieved a test RMSE of 20.140 and an R²-score of 0.8113, indicating it could explain about 81.13% of the variance in the dataset. By the execution of hyperparameter optimization using Optuna, the model showed improved performance, with a test RMSE reducing to 19.56 and the R²-score increasing to 0.8219. But when testing the model on the original dataset (DS001), the testing performance drops significantly to a test R²-score of 0.4852. That results indicate over-fitting to the synthetic dataset and a lack of generalization to the original dataset. Also, similar results were achieved for ID05 and ID06 by testing the dataset DS012 which consist also of mixed synthetic data from the years 2019- 2021.

ID07 and ID08 (DS013): For ID07 and ID08, a combined dataset (DS013) incorporating both original and synthetic data spans from 2016 to 2024 was created. The initial model demonstrates low satisfactory training performance with an R²-score of 0.5911 but still achieves lower testing performance with an R²-score of 0.5786. After Bayesian

optimization, the training R²-score improves significantly to 0.7589, and testing R²-score increases to 0.7299, indicating better generalization. When tested with the original dataset, the testing R²-score achieves a moderate value of 0.6385, reflecting some improvements in robustness compared to purely synthetic datasets

ID09 and ID10 (DS002): After further analysis, an improved feature engineering was done by including additional features on the existing data set. Data was aggregated based on Unique ID for each day to enhance model performance and reduce the number of data points. For ID09 and ID10 the dataset (DS002) spans from 2022, to 2024, mirroring DS001 with an identical period and an adapted data count of 18,625 points based on the improved feature engineering. ID09 utilizes a Random-Forest Regressor, which shows robust performances with test R²-score of 0.8025 and test RMSE of 16.545, which indicate a high accuracy. In ID10, the XGBoost Regressor optimized with Optuna was used, which shows slightly improved performance with test RMSE of 16.37026 and test R²-score of 0.8119. This small enhancement confirms the utility of hyperparameter optimization via Optuna, which fine-tunes the model to capture small improvements.

Furthermore, an overview of the model performance of ID10 is presented in a scatter plot in Fig. 5. which shows the results of the model predictions in comparison to the real values. The values are defined in kilograms. The blue dots scattered across the graph depict individual predictions against the actual quantities. The dashed red line represents the ideal scenario where the predicted values perfectly match the actual values. While the model performs well for a broad range of values, it tends to slightly under predict the higher quantities.

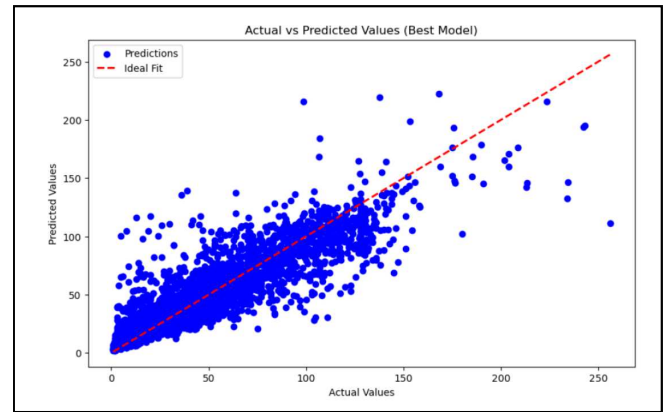


Fig. 5. Scatter plot of the results of ML pipeline ID10 for product quantity prediction

Additional to that, Fig 6. illustrates the cumulative feature importance for the ML pipeline with ID10. The bars which represent the individual features are plotted in order of importance, beginning with the most influential. The length of each bar indicates the relative impact of each feature on the model's predictions. The diagram shows that the model is highly dependent on two features which are representing information of the supplier, variety and geographical field location. Also, the peak areas depending on variety, altitude and region is influencing the model results.

In summary the selected model exhibits only minor deviations in predicting product quantities and predominantly succeeds in representing real events. However, at high product

quantities, the model tends to underestimate lower product quantities.

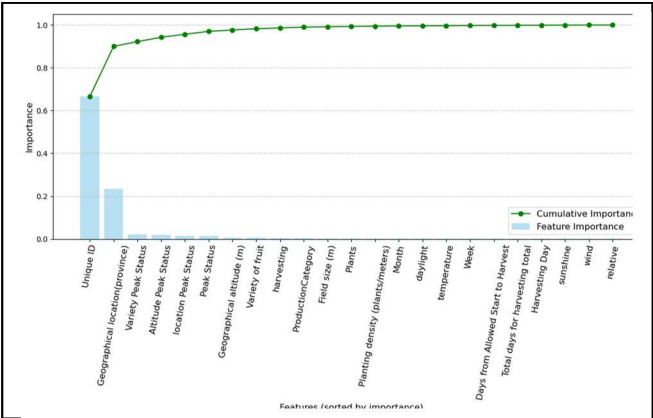


Fig. 6. Cumulative feature importance of ML pipeline ID10 for product quantity prediction

2) Quality prediction

Based on the results of the ML pipeline for predicting product quantity, the ML pipeline for predicting product quality was developed. The results of the various ML pipeline set ups are presented in Table 2 and will be described below. The percentage value of the products with the specific quality level of the total provided quantity is calculated as the target variable. The predictions are made on a weekly basis and take into account quality types 1 to 4. In contrast to the other four levels, no specific model was developed for quality level 5, as products of this quality level are defined as waste.

TABLE II. RESULTS OF THE DIFFERENT ML PIPELINES FOR PRODUCT QUALITY PREDICTION (IN PERCENT FROM TOTAL PRODUCT QUANTITY)

ID	Dataset ID	Total Data Count	Quality Type	Feature Set	Training Model	Test RMSE	Test R2	Training RMSE	Training R2
11	DS003	3696	1	D	XGBoost Regressor	13.481	0.5906	8.63	0.8161
12	DS003	3696	1	D	XGBoost Regressor + Bayesian	13.3041	0.6013	5.4431	0.92692
13	DS014	7368	1	E	XGBoost Regressor	11.43	0.6907	9.0833	0.8017
14	DS014	7368	1	E	XGBoost Regressor + Optuna	9.6340	0.7803	0.8509	0.9982

ID11 and ID12 (DS003): In ID11 and ID12 the used dataset (DS003) builds up on the DS002 dataset and was enriched with additional features which are important for the quality prediction and was already mentioned in III.B. The dataset includes 3696 data points from 2022 to 2024. For the ML pipeline, the model XGBoost Regressor with Bayesian optimization was used. The initial model using the XGBoost Regressor demonstrated moderate performance, with a train R²-score of 0.8161 and a test R²-score of 0.5906, suggesting that while the model was performing well on the training dataset, the model struggled to generalize these findings effectively to the testing data. The model shows signs of overfitting. After applying Bayesian Optimization, an enhancement in model parameters led to improved performance metric with a train R²-score of 0.9269, and test R²-score of 0.6013. The model became better at capturing the nuances of the training set but still is not able to generalize.

ID13 and ID14 (DS014): The ID13 and ID14 pipeline use the dataset DS014 which consist of the DS003 and an additional mixed synthetic dataset with a time span from 2019 to 2021. Based on that the DS014 consist of 7368 data points from year 2019 to 2024. Initially, the model performed reasonably well, achieving a train R²-score of 0.8017 and a test R²-score of 0.6907. After applying Optuna Optimization, the train R² increased to 0.9982, and the test R²-score improved to 0.7803. The reliance on synthetic data alongside original data significantly boosted performance. However, further refinement of the synthetic dataset quality could potentially enhance the model’s robustness.

Given the limitations in predicting the exact quality percentage for a specific supplier, the parameter for the prediction output was changed to the specific value of total weight per quality per week. This step aims to achieve directly measurable and operationally relevant results: Initial tests show the performance results of the selected model to predict the specific value for quality class 1. The achieved results are presented in Table 3 and will be presented below.

The data set DS004 was used to train and test all different model configurations (ID15-ID22) of the XGBoost regression for predicting the different quality types. A separate XGBoost regression model was developed and trained for each quality type. The developed models predict the product quality in kg for one week for the respective quality type.

ID15&16 (DS004): The ID1 and ID2 pipeline is using the dataset DS004 to predict the raspberries in kg for the quality class 1. The model initially exhibited robust performance with a train R²-score of 0.9881 and a test R²-score of 0.9360. The results indicate that capturing the variance in the training dataset improves model performance not only in the model training. After implementing Bayesian Optimization, there was a slight decline in the training R²-score to 0.9818, and a small improvement in the testing R²-score, which increased to 0.93995. This enhancement in the testing R²-score in comparison to the results before the pipeline and target value adaption demonstrates that the model’s generalization capabilities were strengthened by the optimization process, allowing it to perform more reliably and consistently on new datasets.

TABLE III. RESULTS OF THE DIFFERENT ML PIPELINES FOR PRODUCT QUALITY PREDICTION (AFTER CHANGEOVER TO WEEKLY PRODUCT QUALITY PREDICTION IN WEIGHT [KG] PER QUALITY TYPE)

ID	Dataset ID	Total Data Count	Quality Type	Feature Set	Training Model	Test RMSE	Test R2	Training RMSE	Training R2
15	DS003	3696	1	F	XGBoost Regressor	6.1852	0.9360	2.6318	0.9881
16	DS003	3696	1	F	XGBoost Regressor + Bayesian	5.9919	0.93995	3.2591	0.9818
17	DS003	3696	2	G	XGBoost Regressor	3.780	0.9186	1.3401	0.9884
18	DS003	3696	2	G	XGBoost Regressor + Bayesian	5.9919	0.93995	1.4986	0.9854
19	DS003	3696	3	H	XGBoost Regressor	1.90	0.8103	0.4581	0.9856
20	DS003	3696	3	H	XGBoost Regressor + Bayesian	1.82	0.8240	0.43	0.9895
21	DS003	3696	4	I	XGBoost Regressor	1.53	0.5395	0.3121	0.9695
22	DS003	3696	4	I	XGBoost Regressor + Bayesian	1.42	0.5896	0.29	0.9856

The pipeline results for the other quality types can be seen in Table 3. The models used to predict quality classes 2 - 4 show a lower performance. One possible reason could be the

higher variance of the values of the labeled dataset for those types. This is due to the fact that the clear identification of one of the quality types 2-4 is definitely more difficult for the experts which create the labels than the identification of quality type 1.

Moreover, the performance ID16 pipeline of predicting the product quality for quality 1 in kg by using the XGBoost model optimized with Bayesian running on the DS004 can be seen in Fig 7. It displays the relationship between actual and predicted values for the "Kg Per Quality_1". The dense clustering of points around this line across all value ranges indicates strong model performance, particularly in accurately predicting typical quantities, although there are slight deviations at higher values. In comparison to Fig. 5 the model in Fig 7 reflects the real situation better and shows a low dispersion in the predictions. One of the reasons for this result is the adjustment of the forecasts from daily to weekly basis.

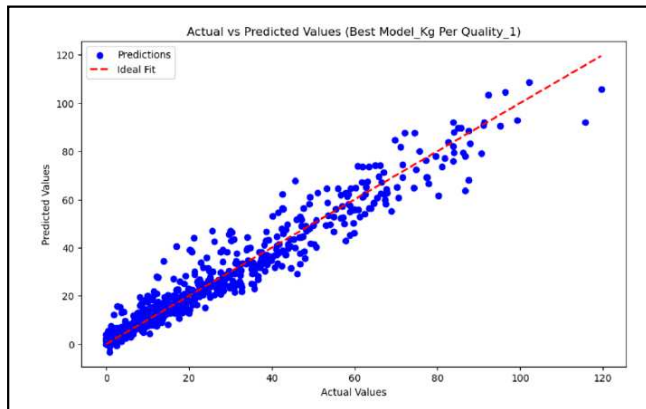


Fig. 7. Scatter plot of the results of ML pipeline ID16 for product quality prediction for quality type 1

Additional to that, the Fig. 8 displays the cumulative feature importance for the ID2 pipeline. The diagram provides an overview of the feature which are influencing the model results. The three features, "Unique ID", "Geographical location" and "Harvesting kg tot" have a high individual importance on the model results with in total 80%. In addition, other features such as "Status Week Quality" and "Variety of Fruit" influence the model results by around 4 to 5 % each. The results show also for the quality prediction that the model prediction is highly dependent on the supplier, raspberry variety, geographical field location and the harvested quantity.

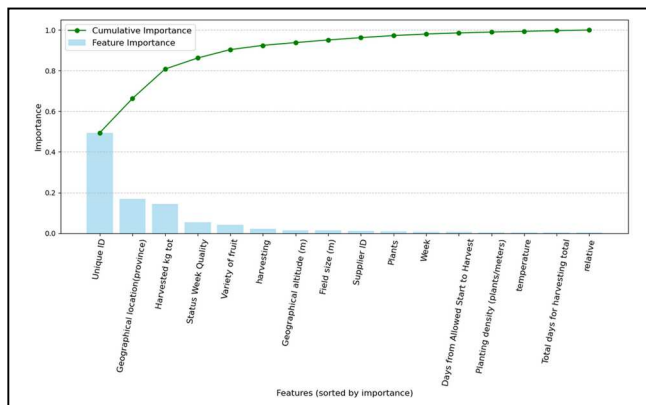


Fig. 8. Cumulative feature importance of ML pipeline ID16 for product quality prediction for quality type 1

B. Discussions

The results indicate that the developed ML pipeline and the utilized models are capable of providing reasonably accurate predictions for product quantity and quality based on the used performance metrics. The ID4 pipeline for predicting product quantity achieved test results with an RMSE of 16.37026 and an R^2 score of 0.8119. The results demonstrate that the model is largely capable of generalizing; however, it will encounter difficulties in accurately predicting all edge cases. The accuracy of the predictions was enhanced through the developed pipelines and various preprocessing steps, yet the results can be still improved.

Additionally, the results from the ID15 – ID22 pipelines highlight the usability of the developed solutions for predicting product quality. In particular, the prediction of product qualities of type 1 can be effectively forecasted by the model. Due to the highly variable values of the quantity of products of quality types 2-4, the model performance in this regard is lower.

To better understand the results, relevant limiting factors are briefly presented below, which should be considered when evaluating the findings.

Two of these factors are the quality and quantity of the available data. Although this has been enhanced through mixed synthetic data, these can only very limitedly incorporate new events into the model training. There is a need for a larger dataset with additional historical data, which will likely further improve model performance. This is particularly important as the plants bear fruit over a longer lifespan with different performance phases. The consideration of production and field data over 2.5 years is thus improvable.

Additionally, it should be noted that the model results obtained are based on the existing dataset. If new suppliers are to be added to the portfolio in the future, the model will require retraining with the adjusted dataset.

Furthermore, some influencing factors that have already been presented in the state of the art have not been included as factors for the ML modeling. This is partly because parameters in the chosen application case are defined as constants, such as soil quality. Additionally, there are parameters that currently cannot be included due to the high effort involved, such as the exact tracking of harvested raspberries per plant.

V. CONCLUSION

The developed ML pipelines show good results for providing valuable prediction for product quantity and quality in an early stage to support the production planner in their daily business. Nevertheless, there is still room for improvements of the ML-pipeline to achieve higher precision in the prediction results not only for the product quantity but also for product quality types 2-4. Moreover, it's important to acquire further production and field data for future retraining of the model to improve the performance.

As one of the next steps, the developed ML pipeline needs to be tested and validated with the expert in the real production setting with actual datasets to analyze the influences and support of the production planner in his daily job. Additional to that, an integration of Reinforcement Learning approach into the developed ML-Pipeline could improve the model usage over a longer period by keeping it up to date with actual

data. With this approach, the model could be trained in daily use by giving the model feedback on whether the prediction was correct or not.

MATCHING & CONTRIBUTION

This paper aligns well with the ICE IEEE 2025 conference theme of "Engineering, Technology and Innovation" and specifically addresses the research area of the special session "Smart grading, handling, and packaging solutions for soft and deformable products in agile and reconfigurable lines". The paper explores the use of innovative ML technologies to predict the quality of raspberry products at an early stage to support the production planner in his daily and weekly ordering and scheduling processes. By using data-driven approaches to analyze historical production data in combination with historical and forecast weather data, the chosen approach provides new useful insights into raspberry product quality and quantity at an early stage. With this solution, production planners can incorporate the information gained into order management to more accurately meet customer requirements and increase customer satisfaction. Due to the high product complexity of raspberries and the large number of influencing parameters, the presented approach increases product and production transparency in a "smart and agile" way that is useful for handling and packaging companies and customers. The paper has demonstrated the relevance of ML-based approaches for early prediction of raspberry product quality and quantity, and could provide valuable insights that will be part of the conference proceedings.

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