Real-time Smart Farming Services

Yield optimization of potato harvesting

Prof. **Wolfgang Maaß**, Deutsches Forschungszentrum für Künstliche Intelligenz, Saarbrücken (DFKI); **Iaroslav Shcherbatyi**, Deutsches Forschungszentrum für Künstliche Intelligenz (DFKI), Saarbrücken; **Sven Marquardt**, Grimme Landmaschinenfabrik GmbH & Co KG, Damme; **Arndt Kritzner**, Logic Way GmbH, Schwerin; **Benedikt Moser**, FIR e.V. an der RWTH Aachen, Aachen

Abstract

Agriculture resembles general production processes in many respects by being "production on the field". Therefore, it is straightforward to apply concepts known by Industrie 4.0 to agricultural environments. In contrast to, for instance, automotive production, agricultural machines are constantly moving while products are rather static during growth phases. Harvesting and logistic processes increase the complexity by moving machines and moving crop. In this highly dynamic environment, sensor data is increasingly collected for any kind of signal, such as machine data (e.g., oil pressure, speed of rotation) and supervision data (e.g., video signals). Data flows in as packages or streams via communication protocols as defined by ISOBUS. Using this increasing amount of data for making decisions in real-time is currently a challenging task.

In this paper, we introduce a framework for processing agricultural data by leveraging on-board computational devices in combination with cloud infrastructures. The concept of smart services is introduced as a means for processing data and providing services to various stakeholders. Special emphasis is given to real-time decision-making. The framework is derived from the more general acatech reference model for the *Smart Services Welt* initiative. Smart service environments are based on generic and domain-specific software-based services. This gives rise to a software market to which incumbents and new entrants will provide software-based services. Of particular interest are data analytical services based on various Artificial Intelligence methods.

The proposed *RESFAST* framework is exemplified by a potato harvesting process. We introduce the concept of a *nPotato* that senses physical impacts during the harvesting process. This data is analyzed locally on a harvesting machine in real-time. Impacts are

categorized and accumulated over time. Farmers are informed about the current accumulated impact so that he/she can act accordingly and adjust machine configurations and driving speed. Furthermore economic forecasting services are used for making market price predictions that, in turn, are combined with impact analyses. Together, farmers receive information about the current status and the predicted return-on-investment. It is shown how data and results are used by cloud services for analyzing across different dimensions, such as geographical areas, time, and crop types.

Collection and analysis of sensor data from an artificial potato

Today's agriculture already uses digital technologies in many areas to optimize the yield from fields, but also in barns. Digital technologies are currently used mainly for machine control and for administrative processes. However, technologies of the Internet of Things and Robotics are increasingly moving into agriculture and enable both the networking of machines and the automated control of agricultural activities in real time. In order to generate a benefit for the farmer, collected data are compacted and offered to the farmer via smart, analytical services [2] in the right situation at the right time.

The example of potato cultivation is investigated by a consortium of research and industrial partners within the framework of the research project Smart Farming World (https://www.smart-farming-welt.de) funded by the German Federal Ministry of Economic Affairs and Energy, as data on physical effects (e.g., beatings), temperature and humidity can be used over the life cycle of a field crop during sowing, harvesting, transport and storage in order to achieve an economically optimal yield. For example, potatoes suffer from high speeds of the harvesters and harvesting belts, which subsequently lead to losses in the crop during storage by putrefaction.

The intelligent "pain-sensitive" potato (nPotato) is a plastic object of the weight and the size of a real potato, which is equipped with sensors for impacts and rotations. Data is locally analyzed on the farm machine by using machine learning methods and provides insights to the farmer in real time. This includes classifying impacts and continuously calculating damage distributions for the crop for the field. Results are linked to a second statistical method, which uses historical potato prices over the past few years to forecast monthly average prices for the next three individual months. The results of both services are integrated into a projected financial return. This allows the farmer to always access the predicted yield value of the current crop for the next three months. If the forecast is below the target yield, the farmer can make direct contact with the driver of the machine in order, for example, to chance the set up of the harvesting machine or remove obstacles.

Realt-time Harvesting Analysis

The nPotato detects acceleration and rotation events in real-time in order to convert these into the potato according to the type of potato, which in turn are classified. The classification is carried out by means of a deep learning model, which was trained in advance via fall experiments. In this experiment, potatoes of a certain type are dropped from different heights onto a smooth metal surface. The potatoes are then peeled, deep-fried, and checked by experts at the pits. The results are incorporated into the learning process of the deep learning model. The parameters of the model are transferred to the computational units of the potato harvester and thus are available as a classification mechanism (see Fig. 1).

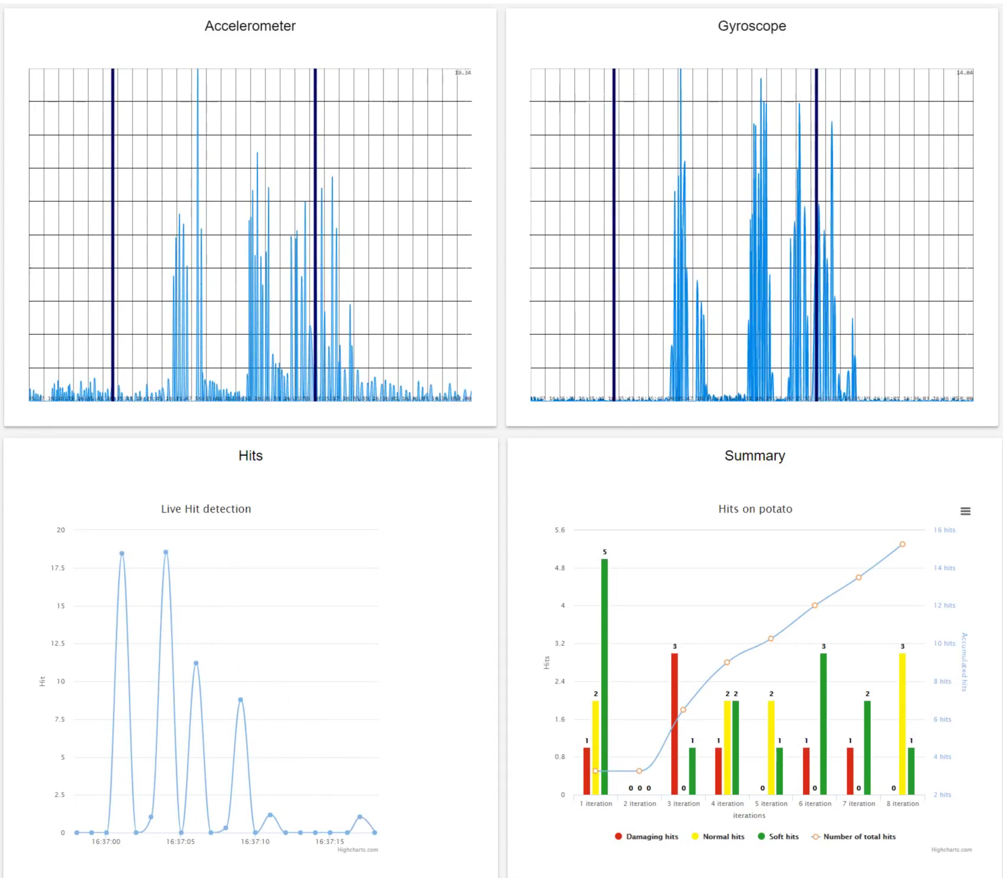

Fig. 1: Upper part: raw data on accelerations (left) and rotations (right) of the nPotato; lower part: diagramm with classified impacts (left) and development over time by several iterations in the harvester (right).

Incoming data streams are classified by a deep learning model over a time window of five seconds [4]. Thus the farmer recognizes the collected number of light, medium and strong impacts on the nPotato. Since the nPotato is automatically withdrawn from the harvesting process at the end, this process can be carried out continuously (see Figure 2, top right). Several rounds are integrated via a statistical distribution so that average values can be displayed to the farmer.

Economic Forecasting Model

Based on historical potato price data, another deep learning model was trained. Since the potato market price is subject to daily volatility, which are difficult to predict, we use a long-term prediction of monthly averages relative to the day of the harvest, i.e., the monthly average prices of the next month, the second month and the third month after harvest. Together with the proportion of undamaged potatoes, it is also possible to predict what the total profit can be achieved. By linking to a farm management system, the production costs and thus the pre-tax (EBT) result can be determined for a particular field (see Figure 3) [5]. This gives farmers the opportunity to act more autonomously, which strengthens their market position.

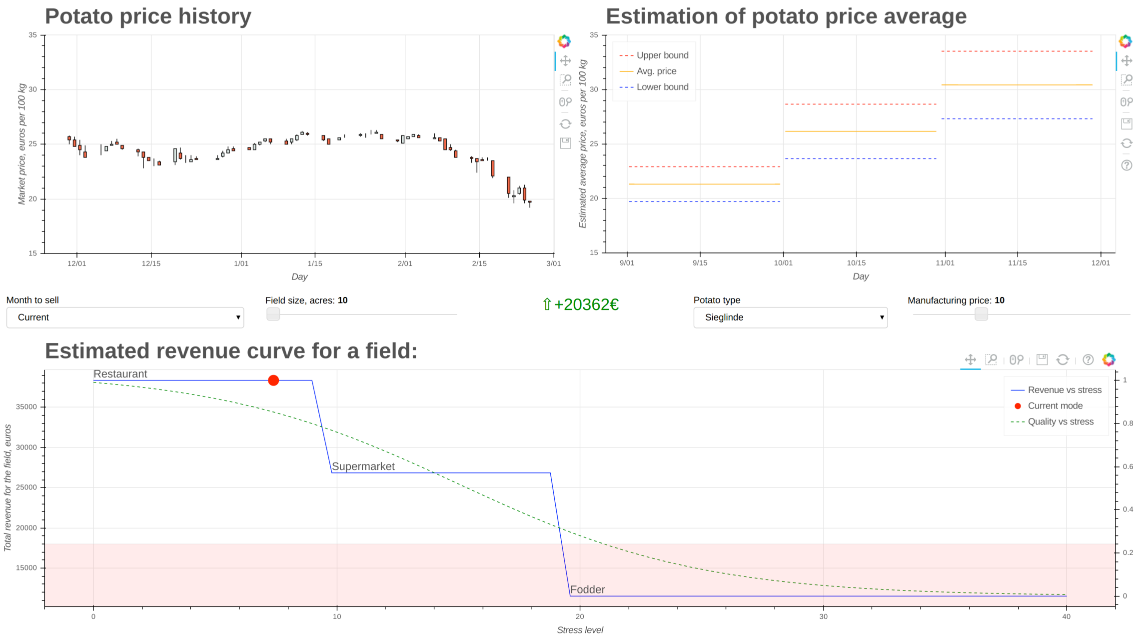

Fig. 2: Yield service for different sales classes (quality grade I, II and III)

The graduation is carried out using quality grades. Quality class I are products of good quality with slight defects, quality class II are marketable with permissible errors, whereas quality grade III potatoes are only used as animal feed and consequently yield a lower yield. Too many strong impacts on potatoes cause the product to slip into quality class III. In the example in Fig. 2, this is equivalent to an economic loss for the considered building field.

RESFAST Platform and Technical Architecture

The analysis of the potato movements during the harvesting process, the transport and storage, the prediction of medium market prices and the integration of the two analyzes are respectively smart services, which analytically consolidate captured data in real time and offer it in the form of digital services. These smart services are part of the "Realtime Smart Farming Services" platform (RESFAST) (see Figure 4). The goal of RESFAST is the rapid development of new smart-farming services, which work on different data streams. RESFAST couples local analysis on the agricultural machine with central cloud services.

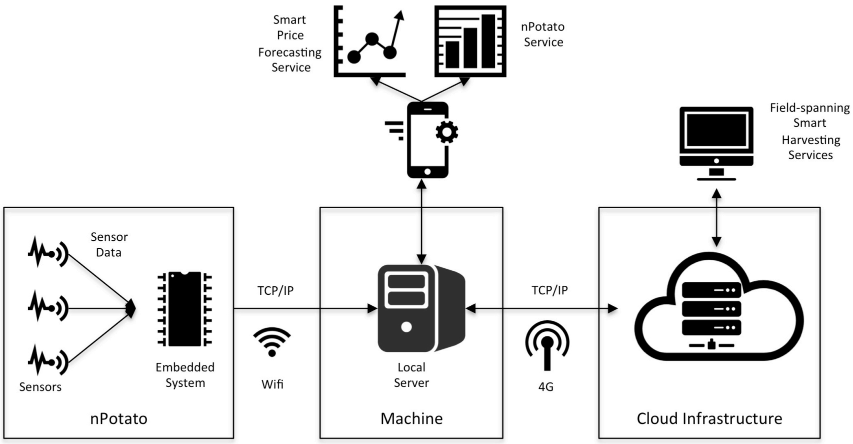

Fig. 3: RESFAST architecture

The nPotato forecast service determines damages directly on the basis of sensory data. With the combination of decentralized smart services and cloud services, the modern farmer can always see the state of the harvest. Because the RESFAST architecture is vendor-independent, the platform can be used across different machines. Thus, the farmer can increasingly make operational decisions in real time to reduce his entrepreneurial risk.

On the RESFAST platform, third-party generic and specific smart services can be installed and linked together. Smart services support the business processes and take account of the organizational structure of role concepts via a web-based authorization process (supported by OAuth 2.0). Thus, RESFAST provides a smart service platform on which data-driven smart agriculture can be efficiently implemented.

Summary and outlook

Farming companies are increasingly generating more data through intelligent machines and other sensor units, which can be evaluated by smart farming services and made available to the modern farmer as knowledge and decision-making aids in real time. As a result of the increasing automation, entire production processes can be optimized over time by adapting networked smart services to the processes and decisions of the farmer and optimizing the overall system. This, in turn, is the basis for the use of agricultural robots, resulting in a further strengthening of the automation of agriculture in the long term. Such an agricultural robot could, for example, an autonomous harvesting machine for potatoes, which takes decisions on the basis of the information obtained from the nPotato independently and makes settings. However, the use of nPotato as a sensor node and smart service does not have to be confined to the harvesting phase of potatoes. Technological advances that lead to a significantly lower energy consumption can ensure that the nPotato is already integrated into the field during the sowing of the regular potatoes and thus runs through the entire life cycle. The nPotato thus becomes the digital shadow or product memory of a potato. On the one hand, the entire value chain of potato production can be optimized and on the other hand the transparency for the end user can be drastically increased. In the future, however, not only the potato will have a digital shadow. Also conceivable are digital twins of other field crops such as corn or lettuce. The use of smart services in agriculture is just beginning and holds great potential for the future.

[1] Hu, Y. C.; Patel, M.; Sabella, D.; Sprecher, N.; Young, V. (2015): Mobile edge computing. A key technology towards 5G. ETSI White Paper, 11 (11) (2015), S. 1-16.

[2] Kagermann, H.; Riemensperger, F.; Hoke, D.; Helbig, J.; Stocksmeier, D.; Wahlster, W.; Schweer, D. (2014): Smart Service World: Recommendations for the Strategic Initiative Web-based Services for Businesses. Berlin: Acatech-National Academy of Science and Engineering.

[3] Quigley, M; Conley, K.; Gerkey, B.; Faust, J.; Foote, T.; Leibs, J.; Wheeler, R.; Andrew, Y. Ng. (2009): ROS: an open-source Robot Operating System. In: ICRA workshop on open source software, (3) 2009, S. 5.

[4] Schmidhuber, J. (2015): Deep learning in neural networks: An overview. Neural networks 61 (2015), S. 85-117.

[5] Sørensen, C. G.; Fountas, S.; Nash, E.; Pesonen, L.; Bochtis, D.; Pedersen, S. M.; Basso, B.; Blackmore, S. B. (2010): Conceptual model of a future farm management information system. In: Computers and Electronics in Agriculture 72 (01) (2010), S. 37-47.