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Machine Learning For Supply Chain Food Safety

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This research (work, forum, program, etc.) was funded by Walmart Foundation (Project # 61626817) and supported by Walmart Food Safety Collaboration Center.

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Deep Learning in Food Safety

- Our ability to record and store data has exploded
- Raises possibility for more advanced analysis than previous methods
- Deep learning can help automate analysis process, make use of big data, and augment human analysts

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Why Deep Learning?

- Deep learning can find complex relationships hidden in the data
- Traditional analysis techniques require you to know the kinds of relationships you are looking for
- Deep learning can handle very complex data like images and video
- Capabilities of deep learning and neural networks are rapidly advancing

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Uses of DL in Food Safety

- On process and transport data for anomaly detection
- Optimizing process parameters, machine control
- Inventory management
- Routing and demand anticipation
- Risk assessment and management
- Visual inspection of product
- Visual monitoring of facilities
- Visual monitoring of livestock
- Visual monitoring of processes

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ML at different levels

- In the European milk supply chain, a ML model identified correlations between national indicator variables and food safety risks more than a year later[1]
- In China, a graph-based spatiotemporal deep learning model was developed to determine the risk of foodborne disease in the next month in 4 different provinces outperforming traditional statistical methods[2]
- In China, ML models were shown to greatly (from 20% accuracy to F1-score .96) improve determining true outbreaks from case reports over prior rule-based screening methods[3]
- In China, an ML model was trained to predict pathogen in specific cases of poisoning. Natural-language processing workflows were used to improve coverage and accuracy of case reports (e.g. connect "hot pot" to "beef" and "mutton")[4]
- In a pharmaceutical case study, a multiple stage ML model for phase and criticality labeling was developed for a multi-phase production process without labeled phases.[5]

Sources: 1: Liu, Ningjing & Bouzembrak, Yamine & van den Bulk, Leonieke & Gavai, Anand & Heuvel, Lucas & Marvin, H.J.P.. (2020). Automated food safety early warning system in the dairy supply chain using machine learning. 10.21203/rs.3.rs-119633/v1.
2: Du Y, Wang H, Cui W, Zhu H, Guo Y, Dharejo F, Zhou Y. Foodborne Disease Risk Prediction Using Multigraph Structural Long Short-term Memory Networks: Algorithm Design and Validation Study. JMIR Med Inform 2021;9(8):e29433. DOI: 10.2196/29433
3: :Zhang, Peng & Cui, Wenjuan & Wang, Hanxue & Du, Yi & Zhou, Yuanchun. (2021). High-Efficiency Machine Learning Method for Identifying Foodborne Disease Outbreaks and Confounding Factors. Foodborne pathogens and disease. 18. 10.1089/fpd.2020.2913.
4:Wang H, Cui W, Guo Y, Du Y, Zhou Y. Machine Learning Prediction of Foodborne Disease Pathogens: Algorithm Development and Validation Study. JMIR Med Inform 2021;9(1):e24924. DOI: 10.2196/24924
5. Quatrini, E.; Costantino, F; Di Gravio, G.; Patriarca, R. Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. (2020). Journal of Manufacturing Systems, Volume 56, Pages 117-132, ISSN 0278-6125. https://doi.org/10.1016/j.jmsy.2020.05.013.

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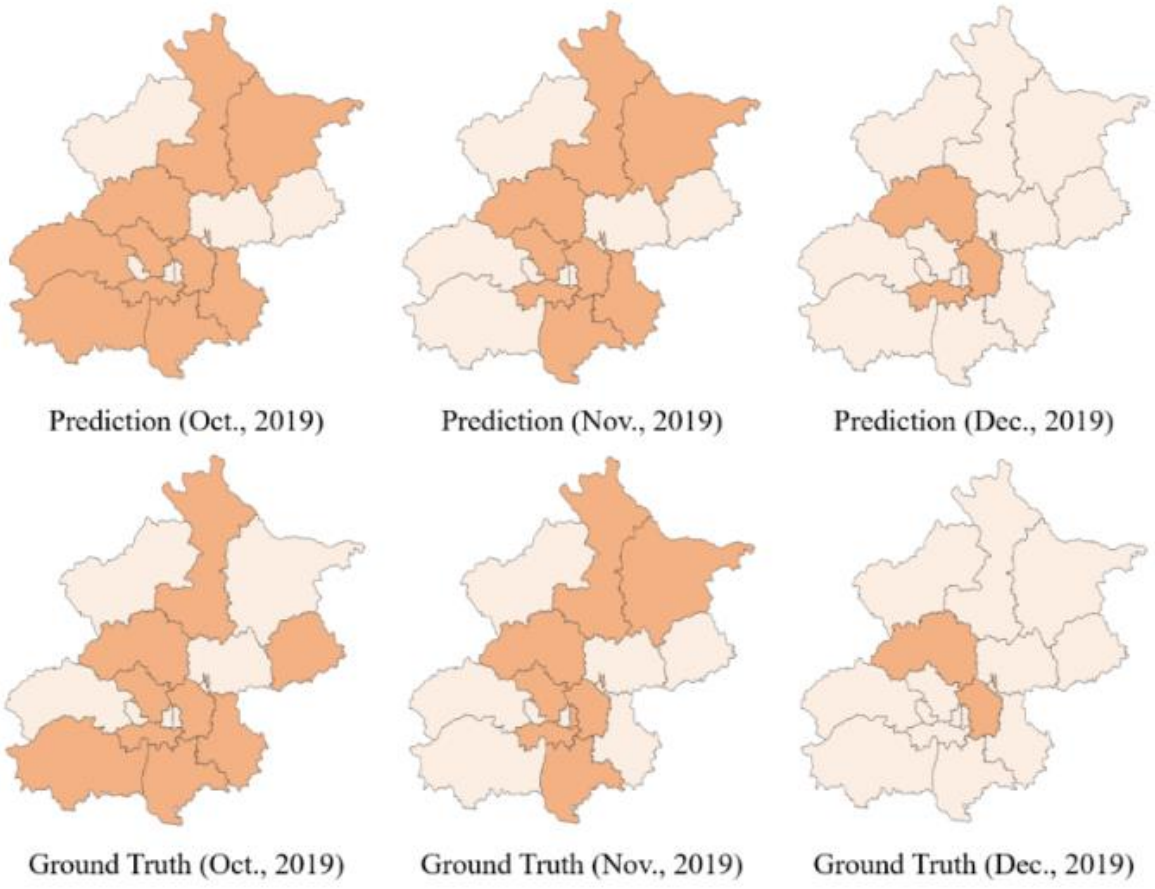
Spatiotemporal Recognition

Figure 5. Case study 1: The first row displays the predictions and the second row displays ground truths for Beijing in October, November, and December in 2019.



Source: Du Y, Wang H, Cui W, Zhu H, Guo Y, Dharejo F, Zhou Y. Foodborne Disease Risk Prediction Using Multigraph Structural Long Short-term Memory Networks: Algorithm Design and Validation Study. JMIR Med Inform 2021;9(8):e29433. DOI: 10.2196/29433

More examples

Folio3 & Livestock management

Folio3 has been working for the automation of various tasks that involves well being of livestock. In addition to developing conventional software, Folio3 recently has taken advantage of rising use of artificial intelligence, machine learning, computer vision and AI powered programmable drones like DJI drone series

Cattle Health

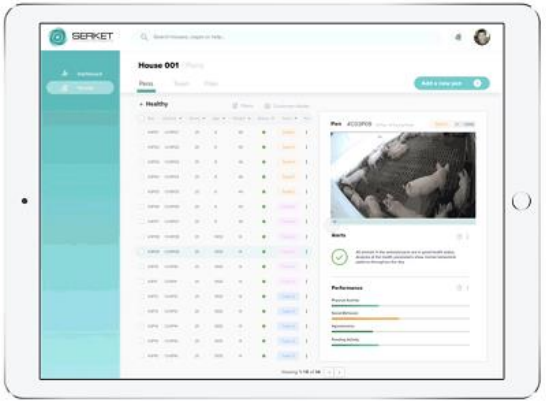
A calm cow, is a productive cow. Our proprietary solution CattlePal is designed specially for the well being of livestock. Drones mounted with thermal camera collects animal's data and send it to cloud servers. Our smart camera system collects video data onsite, which is then used for supervised training.

Piguard

Piguard is an innovative Livestock Management Software that functions based on image recognition and deep learning algorithms. The technology monitors health status by analyzing the behavioral patterns of your animals.

PIGUARD

All in one solution



Sources: https://www.serket-tech.com/Products
https://flox.ai/
https://www.folio3.ai/livestock-management/

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Anomaly Detection

- Supervised machine learning requires labeled data
- Labeled data is often hard to come by
- Anomaly detection is a type of unsupervised learning that can be used even without labeled data
- Using purely features, the system learns to identify “typical” input – and can alert humans when atypical input is detected

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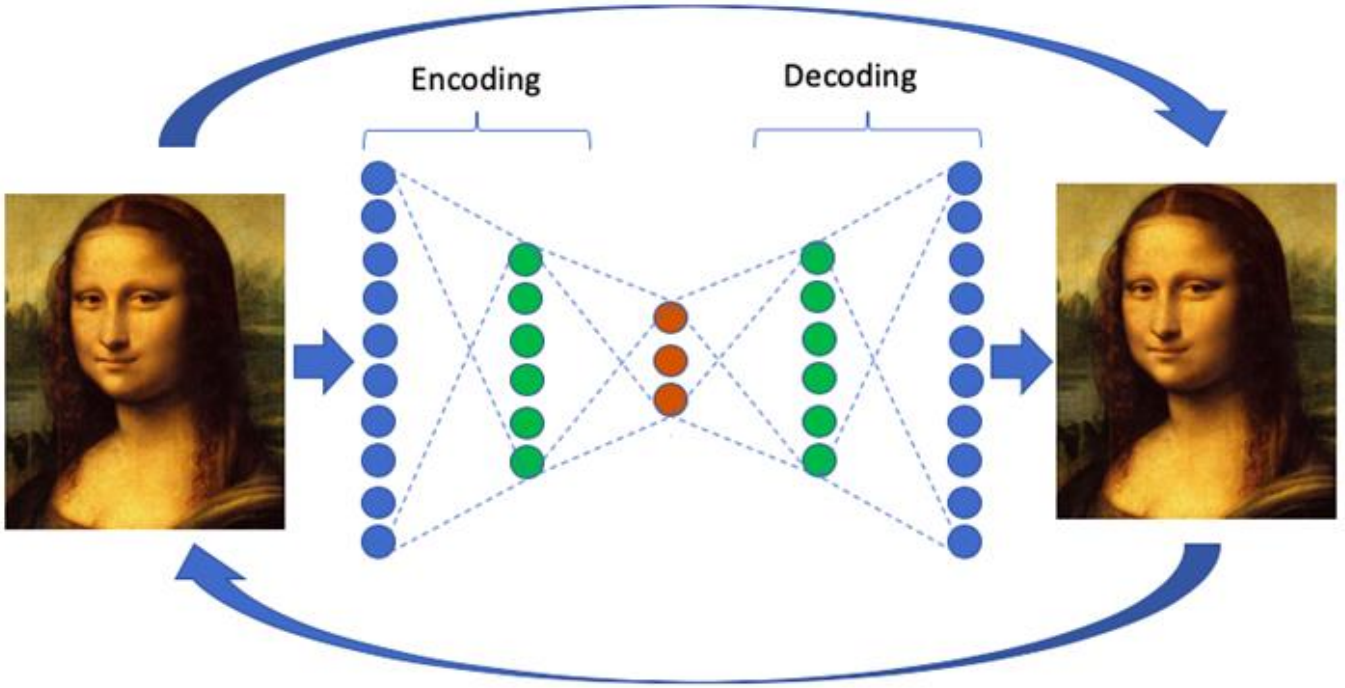
Anomaly Detection Example

- Autoencoders use deep learning to package and reconstruct input data
- If a well trained autoencoder can't reconstruct the input, the input is likely anomalous



Source:https://towardsdatascience.com/anomaly-detection-with-autoencoder-b4cdce4866a6

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Data Integration