# 21st Century Meat Inspector – Project Report

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# 1. Summary

Poultry is the most widely consumed meat in the UK, and its effective inspection within processing facilities is essential to ensure regulatory compliance. Poultry inspection is performed manually and is extremely challenging due to the short time available to inspect each bird and the sustained level of concentration required.

This feasibility project investigated how existing and new inspection technologies can be combined with advanced data analytics and incorporated into current meat inspection practices to deliver the 21st Century Meat Inspector.

The feasibility project focused specifically on post-mortem inspection of poultry, adopting a benefits realisation approach to determine the requirements for any new technologies and ensure that business benefits are delivered to all stakeholders within the poultry chain.

This interdisciplinary feasibility project included expertise in a variety of complimentary inspection technologies (Optical (visual, Near-Infrared, Infrared, Hyperspectral), X-ray and Ultrasonic) and IT-enabled benefits realisation management with the Hartree Centre (STFC), a food business operator (referred to throughout as Food Co.) and CSB as project partners.

The main findings of the project include:

- The main requirements for any new digital technologies to assist meat inspectors (MIs) and poultry facilities were identified as: clear business benefits; robust and reliable; easy to use and clean.
- Deep learning can be used to identify abnormal colour from carcass images with a sufficient number of training images, but more efficient data labelling methods are required.
- Hyperspectral optical and X-ray imaging methods can identify quality issues such as wooden breast and white stripe in chicken breasts.

# 2. Introduction

Chicken is the most widely consumed meat in the UK and used in a variety of meals and products ranging from Sunday roasts to salads, sandwiches and curries[1]. To meet this demand, in 2019, approximately 20 million chickens are slaughtered every month in the UK[2]. The primary processing of poultry typically includes the following steps: pre-slaughter, slaughter, scalding/plucking, evisceration, chilling, and cutting. EU regulation 854/2004[3] specifies that every slaughtered bird should undergo a Post-Mortem Inspection (PMI). This inspection should be performed by qualified meat inspectors (Official Auxiliary) on the carcass and offal of the bird. The meat inspectors operate under the responsibility of an Official Veterinarian (OV). Any birds identified to have signs of disease should be removed for a more detailed inspection by the OV. Also, the OV should perform a detailed inspection on a random sample of birds every day. PMI is a task that has always been performed manually yet has numerous challenges. Due to the large volume of birds processed at fast line speeds, meat inspectors only have a limited amount of time to inspect each bird. one Food Co. facility slaughters 250,000 birds a day and has two full-time meat inspectors working on each of their two processing lines. These inspectors must maintain a high level of concentration during their shift, but human error is possible given the volume of processing. Human inspection is also limited to visible inspection only and is a subjective decision based on the opinion and experience of the meat inspector.

Another aspect of poultry processing that requires detection is birds that are Dead on Arrival (DOA). EU regulation 2019/627[4] stipulates that meat is unfit for human consumption if it is from a bird which was dead before the slaughter phase of the process. Birds that are DOA are identified by operators tasked with placing the birds in shackles and are determined by the temperature of the bird. However, this is becoming increasingly challenging with new slaughter methods such as controlled atmosphere stunning, which occurs whilst the bird is still within its arrival container.

The world is experiencing the fourth industrial revolution (Industry 4.0) which is focused on the use of Industrial Digital Technologies (IDTs) within production environments to deliver economic and environmental benefits through enhanced productivity and efficiency. Industrial digital technologies include sensors, information technologies, robotics, augmented/virtual reality, and artificial intelligence (AI) and are underpinned by the enhanced collection and use of data. Despite IDTs having a predicted benefit of £55 billion to the UK Food and Drink manufacturing sector over the next decade[5], their adoption has been significantly lower than other sectors (for example, aerospace and automotive). This lack of adoption has often been attributed to factors such as the levels of complexity within food materials and production processes and limited resources and expertise required for innovation. The latter is especially the case for small and medium-size enterprises that are prevalent within the sector. Another critical factor is how manufacturers select the most suitable new technologies to adopt, and how the business benefits are evaluated.

Inspection technologies have been developed for applications within poultry processing. Most academic research has focused on optical technologies operating in the visible or near-infrared wavelengths. Much of this previous work has focused on inspecting chicken breasts once separated from the carcass with specific work in detecting quality issues such as wooden breast[6], fatty acid content[7], colour[8, 9] and pH[10]. Research has also been performed related to safety issues, using optical techniques to quantify the number of microorganisms on the surface of chicken breasts[11, 12, 13] and septicaemia in chicken liver[14, 15]. Other works have focused on imaging whole chicken carcasses off-line to identify different issues relating to meat safety[16, 17].

There has been a large body of research, primarily from the USA, focused on online multispectral (and in some cases hyperspectral) imaging technologies to classify birds as either ‘wholesome’ or ‘diseased’[16,18–26]. The majority of this work was performed in pilot facilities, but some research has been performed in full production facilities at line speeds of up to 70 birds a minute. These works generally utilise traditional machine learning classification methods that can identify wholesome or diseased birds with accuracies over 95%. Commercial imaging technologies exist in the UK from companies such as Meyn[27], Marel[28], and Baader[29]. These technologies utilise optical techniques and are used for meat grading or detection of quality issues. The project team visited the Food Co. facility in November 2019. It was found that they utilise optical imaging and X-ray technologies within their primary poultry processing. These technologies are used specifically to detect hock burn, to grade the carcass or to detect the presence of foreign bodies in the final products. During this visit, it was identified that there is also a need for inspection technologies that could identify quality issues such as wooden breast or white stripe in poultry.

Although research and commercially available technologies indicate that online meat inspection is possible, current work has focused on using inspection technology for only a single application (for example, detecting septicaemia or hock burn). There have been no studies that investigate the use of imaging technologies to address several business needs simultaneously or that determine the requirements and benefits from any innovative solutions using appropriate models. All previous work has also been performed outside the EU, where meat inspection guidelines vary. These are the challenges that this project aimed to address.

# 3. Aims and Objectives

This project aimed to assess the feasibility of using sensor technologies and advanced data analytics for poultry inspection. The project planned to focus on PMI and DOA detection and test a range of different sensing technologies at Food Co. and in the laboratory. The project also planned to investigate the use of sensors to detect quality issues within poultry and utilise expertise from the Hartree Centre for advanced image and data analysis. To determine the requirements and benefits of any proposed new technologies, a benefits realisation model has been developed via a stakeholder engagement workshop. This project anticipated several novel aspects including: 1) The use of digital technologies for PMI including offal imaging. 2) The use of digital technologies for DOA detection. 3) A benefits realisation model for sensing technologies within slaughter facilities. 4) The use of advanced machine learning methods (for example, deep learning) for PMI and DOA detection.

Project-specific objectives

- Develop a benefits realisation model to determine the requirements and benefits for poultry inspection technologies.
- Determine the performance of new and existing sensor technologies for PMI.
- Determine the performance of new sensor technologies for DOA.
- Assess the feasibility of combining different sensor technologies and analytics for multiple applications within poultry inspection (for example, PMI and wooden breast).

## 3.1 Project Time Plan

**Table 1: Project time plan**

| Work Packages and Key Tasks (Lead) | Month 1 | 2 | 3 | 4 | 5 | 6 | UoN | LU | UCL | STFC |
|---|---|---|---|---|---|---|---|---|---|---|
| **WP1: Benefits Realisation Modelling (LU)** | | | | | | | Workdays | | | |
| T1.1: Organise site visit and stakeholder workshop | | | | | | | | 5 | | |
| T1.2: Site visit and stakeholder workshop | | | | | | | 1 | 4 | 1 | 1 |
| T1.2: Benefits Realisation modelling | | | | | | | | 35 | | |
| **WP2: Post Mortem Inspection (UoN)** | | | | | | | | | | |
| T2.1: Acquisition of images from Food Co. systems | | | | | | | 22 | | | |
| T2.2: Imaging of PMI at Food Co. | | | | | | | 22 | | | |
| T2.3: Image analysis on data from T2.1 and T2.2 | | | | | | | 33 | | 1 | 4 |
| T2.4: Laboratory trails on internal inspection technologies | | | | | | | 33 | | 2 | |
| **WP3: Dead on Arrival Detection (UoL)** | | | | | | | | | | |
| T3.1: Measurements with the IR system at Food Co. | | | | | | | 11 | | | |
| T3.4: Analysis of recorded IR images | | | | | | | 11 | | 1 | 1 |
| **WP4: Project Management and Future Funding (UoN)** | | | | | | | | | | |
| T4.1: Project management (meetings, registers, plans) | | | | | | | 4 | 2 | 2 | 1 |
| T4.3: Dissemination activities | | | | | | | 2 | 1 | 1 | |
| T4.4: Future funding Plan | | | | | | | 2 | 1 | 1 | |

## 3.2 Project Changes due to COVID19

The ongoing COVID19 pandemic resulted in closures of university laboratories and meant that site visits were not possible at the Food Co. This resulted in the following changes to the project plan:

- Interviews were held online with stakeholders instead of an in-person workshop (T1.1 and T1.2, Table 1)
- It was not possible to perform any imaging at Food Co. site for PMI (T2.2). All other WP2 tasks were completed.
- It was not possible to perform any IR imaging or analysis (WP3, Table 1)

# 4. Methodology

## 4.1 WP1 Benefits Realisation Modelling

This project engaged three main stakeholders.

**Regulator** is a government body responsible for ensuring standards and safety issues are monitored and controlled. For this study, the Regulator is the funder for the project, they provided access to individuals for an interview and a nominated project manager who facilitated all activities and attended project review meetings.

**Food Co.** is a UK based food manufacturing business with several divisions covering an array of food products. One of their divisions focuses on the processing of poultry, which is the area of the business this project is focused on. Food Co. supported this project by allowing access to one of their poultry processing sites for on-site testing of technologies, providing participants for an interview, and providing chicken breasts for lab-based experiments. They also provided a subject matter expert who facilitated all activities and attended project review meetings. They represent an influential organisation within the poultry processing industry, had a strong working relationship with the Regulator, and desired to support research within the industry.

**Software Co.** is a leading provider of services to the food and beverage industry globally, offering complete enterprise resource planning (ERP) systems, including both software and hardware. They have a focus on automation and enabling the effective use of data throughout the enterprise. They supported the project through participation in our research interviews, providing an additional perspective to understanding the broader problem.

### 4.1.1 Data Collection

The primary source of data for this study was interviews with key individuals from across the stakeholder organisations. Newman advocates for careful consideration when choosing participants to ensure those selected are informative. As such, we were careful to include individuals from a range of organisational levels and roles, although we were constrained by the access granted to us by the respective organisations. Table 2 provides an overview of participants and the length of their interviews.

**Table 2: Summary of participants and interviews**

| Interview No. | Organisation | Role | Interview Length |
|---|---|---|---|
| 1 | Food Co. | Food Co. Manager 1 | 60mins |
| 2 | Regulator | Regulator Employee 2* | 28mins |
| 3 | Software Co. | Software Sales 3 | 38mins |
| 4 | Regulator | Regulator Employee 2* | 60mins |
| 5 | Food Co. | Food Co. Manager 5 | 60mins |
| 6 | Food Co. | Food Co. Manager 6 | 60mins |
| 7 | Food Co. | Food Co. Employee 7 | 55mins |
| 8 | Regulator | Regulator Manager 8 | 45mins |
| 9 | Regulator | Meat Inspector 9 | 52mins |
| 10 | Regulator | Meat Inspector 10 | 60mins |
| 11 | Regulator | Meat Inspector 11 | 80mins |

*This person was interviewed twice.

Orientation interviews were carried out with key members from each stakeholder organisation (Food Co. Manager 1, Regulator Employee 2, Software Sales 3) to familiarise them with the project and provide the project team with a better understanding of each organisation's interest in the project. Interviews were recorded with the interviewee's permission.

An interview schedule was designed using categories from the Benefits Management literature and early analysis of orientation interviews to shape the types of questions posed. Key areas of interest were highlighting any tensions between stakeholders, any contradictions or shared concerns in stakeholder needs and understanding the existing issues being faced. The interviews were semi-structured to allow participants to share their insights and for the researcher to maximise the opportunity to explore individual perceptions and experiences, allowing for new questions to emerge. As with preliminary interviews, focused interviews were carried out remotely, recorded with the participant’s permission, and automated caption files were used for coding.

### 4.1.2 Ethics

All participants in this study were asked to complete an informed consent form, supported by a participant information sheet explaining the purpose of the research and how their data would be used. This approach complies with Loughborough University ethic procedures, and this study was approved by the ethics committee before interviews commenced. All interviews were confidential, and data has been anonymised.

#### 4.1.3 Benefits Realisation Analysis

The analysis technique used in this study applied a benefits realisation lens to inform the analysis.

Benefits Management is a process of ensuring potential benefits of Information Technology (IT) usage are achieved. A "benefit" in this context is a measurable outcome from IT usage, which is valuable to stakeholders and organisations. Benefits Management is interested in several aspects of the problem.

First, why an IT investment is made (Drivers), for example, IT investment to ensure the Regulator has effective measures in place to gather and use data for informed decisions, as well as promoting greater accountability onto industry for the product they produce, therefore ensuring consumer safety, which promotes confidence in consumer choices.

Second, the goal of the IT investment (Investment Objectives), for example, the proposed investment will increase the effectiveness of quality control, ensuring the highest proportion of products meet or exceed retailers', regulators' and consumers' standards/expectations.

Third, how the IT investment will help to achieve the goal (Benefits), for example, the inspection process is less strenuous for the meat inspector (auxiliary or vet), chances of human error reduced by automating the identification of a number of quality issues, improve the supply chain by gathering data to feed back into the process to address quality issues from the outset.

Fourth, how the way we work needs to adapt to achieve the goals and use the new IT (Business Change), for example, adjusting the role and responsibilities of the MI, ownership / or management of new IT.

Fifth, what support is needed to roll-out the IT and achieve the change (Enabling Change), for example, training on using and maintaining the new IT and the resulting data and changing the inspection process to embed the new IT into the production line.

Finally, sixth and seventh, what will help and what will hinder the success of an IT investment (Facilitators and Inhibitors), for example, improving the day-to-day work of the MI and reducing stress, or fear that the new IT may negatively impact jobs.

Early benefits management analysis was done soon after the orientation interviews to ensure use of appropriate terminology, and to identify high-level themes to explore and use in subsequent interviews. This high-level coding was performed using NVivo using transcripts that were generated from the automated caption facility in MS Teams. These codes provided the foundation for a codebook.

After undertaking the main data collection interviews, the automated caption transcripts were coded using the codebook in NVivo. These codes were then organised in a matrix display that included each of the BRM categories (Drivers, Benefits, Facilitators etc.) and the coded interview data were mapped to these categories.

## 4.2 WP2 Post-Mortem Inspection

### 4.2.1 Deep Learning Analysis of images

All images were provided by Food Co. and taken from a grading camera system and focused on skin colour. Images were provided in three batches, each batch recorded on a different day and with a different amount of images (Table 5). Details on the origin of the birds were not provided for each batch. It should be noted that the grading camera was down stream of the PMI so any birds identified to have specific conditions will have been removed. However, the purpose of this preliminary work was to determine if deep learning methods could be used to identify differences between birds from images provided from on-site imagining. Skin colour was chosen as the focus area as some poultry conditions (for example, abnormal colour) are related to colour. Supervised machine learning methods such as the deep learning techniques used in this work required labelled data to train the models. The image analysis work in this project was based on identifying birds which had darker than average skin or areas of red (Figure 1 and Figure 2) and each image was labelled normal or dark/red by University of Nottingham researchers. For each batch the data was split into training, validation and test sets. Training data is used to train the deep learning model and validation to tune the hyper- parameters. The test data is used to provide an assessment of the model's performance with data not used in the training or validation.

**Table 3: Batches of chicken taken at different times**

| **Batch 1** | **Training** | **Validation** | **Test** |
|---|---|---|---|
| Normal | 134 | 58 | 81 |
| Dark/Red | 50 | 22 | 40 |

| **Batch 2** | **Training** | **Validation** | **Test** |
|---|---|---|---|
| Normal | 717 | 307 | 432 |
| Dark/Red | 361 | 155 | 270 |

| **Batch 3** | **Training** | **Validation** | **Test** |
|---|---|---|---|
| Normal | 440 | 188 | 464 |
| Dark/Red | 185 | 79 | 181 |

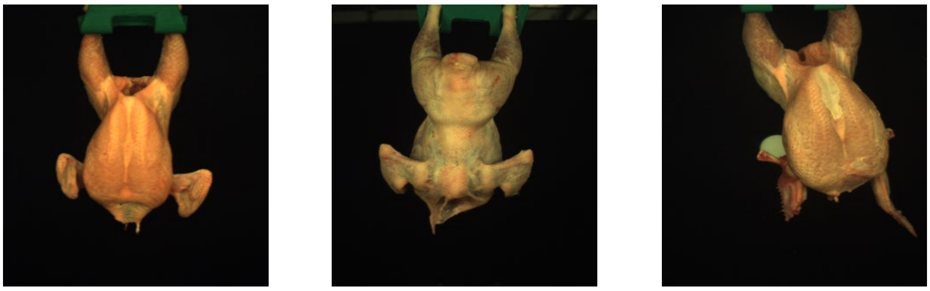


Figure 1: Images from grading camera labelled as normal skin colour

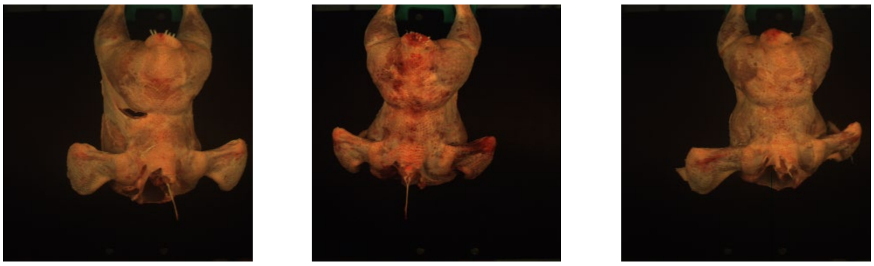


Figure 2: Images from grading camera labelled as dark or red areas

Image analysis was performed using the ResNET and AlexNET Convolutional Neural Networks (CNN) in MATLAB. These types of CNNs were chosen as they have relatively simple architecture, and less computational time. Consequently, they are easy to train especially in limited GPU computers. Convolutional Neural Networks are a deep learning method with built-in convolutional layers which act as feature extractors to train the models.

The ResNET 18 CNN was used with the following parameters:

- Down sampling and image augmentation was used to address the challenge of an unbalanced dataset (far fewer images labelled as dark/red)
- 18 total layers containing 5 convolutional layers followed by 13 fully connected layers
- Learning rate used = 1x10-5

AlexNET was used with the following parameters:

- Image augmentation was used to address the challenge of an unbalanced dataset (far fewer images labelled as dark/red)
- 8 total layers containing 5 convolutional layers followed by 3 fully connected layers
- Learning rate used = 1x10-5

### 4.2.2 Quality inspection Using X-Rays

Transmission X-ray computed tomography (CT) images of the whole breast portions were captured using a microfocal X-ray source (X-Tek SR125) and a flat panel detector (Rayence 1215A). Forward projection images (for example, Figure 3 left) were collected at 1° intervals and 3D images (for example, Figure 3 right) were reconstructed by standard filtered back projection. The relatively thick pieces of chicken combined with the poor low energy response of the panel detector required that high energy (100 kVp) X-rays were used to penetrate the samples. As a result, the contrast in the projection images was poor which means the reconstructed images fail to show internal structures.

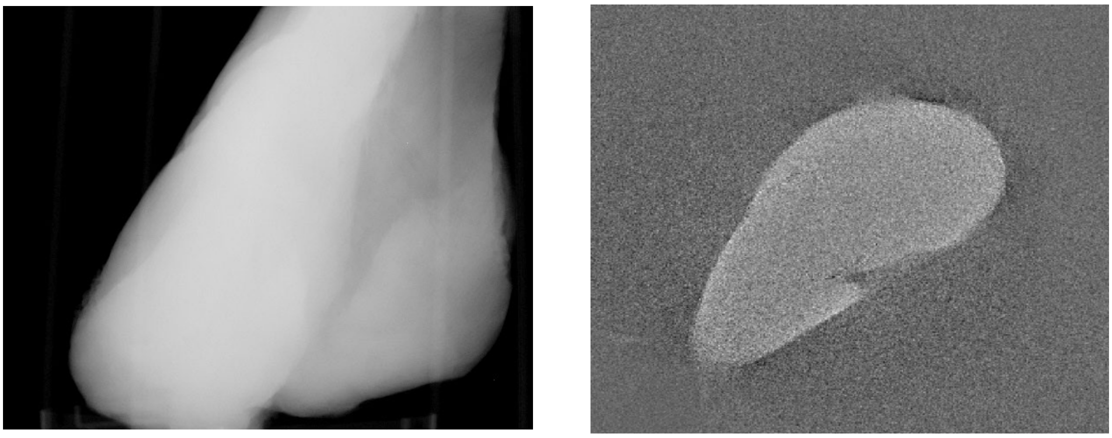


Figure 3: Left) transmission X-ray of chicken breast and Right) reconstructed slice failing to identify any internal structures

To overcome this limitation, we collected further X-ray CT images using a different instrument which has the same X-ray source but a detector that is more sensitive to contrast at lower kVp. In this case samples were cut into smaller pieces (disks of 50 mm diameter) in order to fit into field of view. The smaller samples were packed into a custom 3D printed holder to ensure consistency as shown in Figure 4 top. This technique was more successful in identifying internal features and showed the effects of wooden breast on the internal structure of the tissue.  Figure 4 bottom left and bottom right show a comparison between a fillet affected by wooden breast and a normal control respectively. Wooden breast is a muscle quality disorder which results in regions of increased firmness in the breast. The wooden breast specimen demonstrates a greater degree of texture (indicated by the red arrows) where there are quasi-periodic transitions between higher and lower density tissue over length scales of a few mm. The control sample is overall more homogenous with a consistent internal structure. A number of control and wooden breast samples were measured (4 of each) and similar features were observed in each.

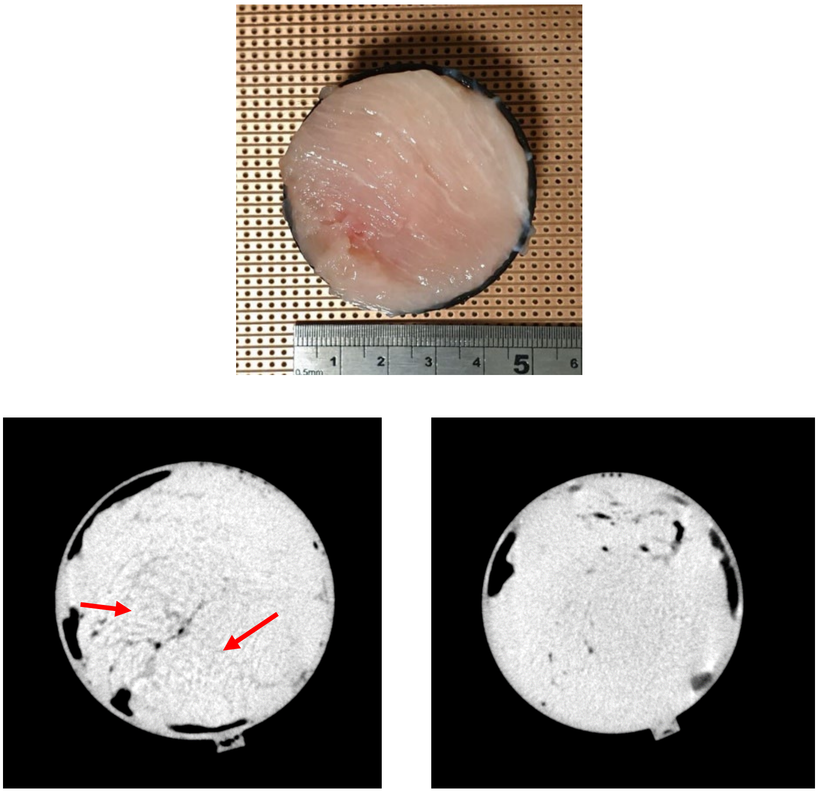


Figure 4: Top) Example of prepared sample, and reconstructed CT slice of bottom Left) wooden breast and bottom Right) control sample.

While transmission X-ray imaging is useful for showing variations in tissue morphology (which has yielded some interesting results here), the output is based solely on the samples' affinity for absorbing X-rays. It does not reveal anything about the underlying molecular structure. X-ray diffraction (XRD) is a technique that can be used for this purpose.

To carry out XRD analysis, a cross-sectional slice of each sample was taken at the thickest point (where wooden breast is likely to be most prominent). The section was placed in a 3D printed mesh-like holder (as shown in Figure 5) and diffraction measurements were made at multiple locations across the sample. XRD data were collected in transmission mode. A narrow beam of X-rays was incident on the sample where there were holes in the mesh holder. The X-rays that scattered from the sample were collected using a spectroscopic detector (one that measures energy) and positioned on the side opposite the X-ray source and XRD spectra were produced by summing the detected counts appropriately. The resulting XRD spectra were subjected to principal component analysis (PCA) in order to determine if there were any distinguishing features that could be used to identify different tissue components. PCA is a well-understood technique that can be used to describe the variance in a set of data and can be used to group/separate data that are similar/different. In this case, PCA did not show any conclusive separation which indicates that there is no obvious, unique feature in the XRD spectra related to normal or wooden breast. This is not surprising. In previous work, meaningful results can only be obtained by PCA (and related methods) when constraints are introduced that are based on the physical processes involved, the sample properties and the geometry of the instrumentation.

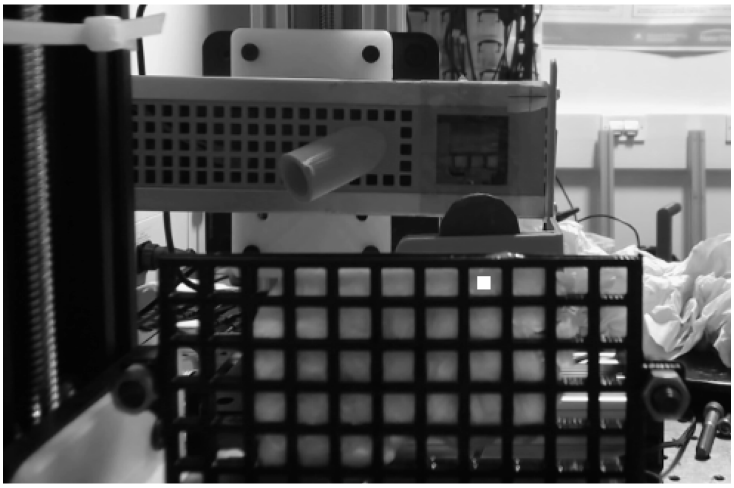


Figure 5: XRD setup showing slice of chicken breast held in place with grid. White square shows location of incoming beam.

**4.2.3 Quality Inspection – Hyperspectral**

Images were recorded using a Near-Infrared (NIR) camera (FX17, Specim, Oulu Finland) operating between the 935-1718 nm wavelengths. This camera is thermoelectric cooled with an Indium gallium arsenide sensor. The camera has an integration time of 3.5 s, 224 wavelength bands, a signal to noise ratio of 1000:1 and produces an image of 981 x 640 pixels with a framerate of 62 frames per second.

Whole chicken breasts samples were images for: healthy (normal), wooden breast, and white stripe. Chopped samples (5x5 cm with the thickness as the whole breasts which varies all over the breast) for: healthy (normal), wooden breast, and white stripe.

Each hypercube data includes 224 images (one per each wavelength) of each sample. For each sample, the image at 1106 nm was used to generate the binary mask image that was applied to all images in the hypercube. The mean reflectance spectra at each band was then calculated. The previous step was repeated on the other bands to form the mean reflectance spectra for the samples.

# 5. Results and Discussions

## 5.1 WP1 Benefits Realisation Modelling

Through the analysis of the in-depth interviews carried out for this project (see Table 2), a Benefits Dependency Network (BDN) diagram was developed (see Figure 6), which illustrates important factors relevant to the realisation of benefits relating to the adoption of IDTs within the poultry processing industry. In this section, each of the categories within the BDN is described, and the context-specific findings for each presented along with supporting evidence.

### 5.1.1 IT Enablers

Five IT enablers were identified when considering the adoption of new technology for poultry inspection. First, any system selected must be simple to use where it requires human interaction. Concerns were raised based on previous failed attempts to install new technology, which had added complexity for the inspector.

This IT enabler is related to two facilitators: technical support from the manufacturer and training in using the technology and new process. These facilitators will be discussed in the following section.

Second, the technology must be reliable. Given the high-pressure environment within which poultry inspection occurs, at large quantities and exceptional speeds, any technology must be reliable "from day one". A particular concern from meat inspectors was that the technology must be at least as reliable as the human inspector, many of whom have decades of experience. Scepticism was raised regarding how feasible it would be for any technology to be capable of the same level of inspection as human inspectors. As such, any technology must be demonstrably reliable from the outset, and there must be a well understood backup if, for any reason, the system should go down. Alternatively, the technologies could be used to augment the current meat inspector task to reduce the burden on the workforce. The impact of stopping the line has implications throughout the supply chain, the welfare of those still in containment (they are alive when they arrive at the plant), through to the plant line where birds need to be in the chiller and scalding areas for defined periods. Any changes to these timings can mean the loss of vast quantities of product.

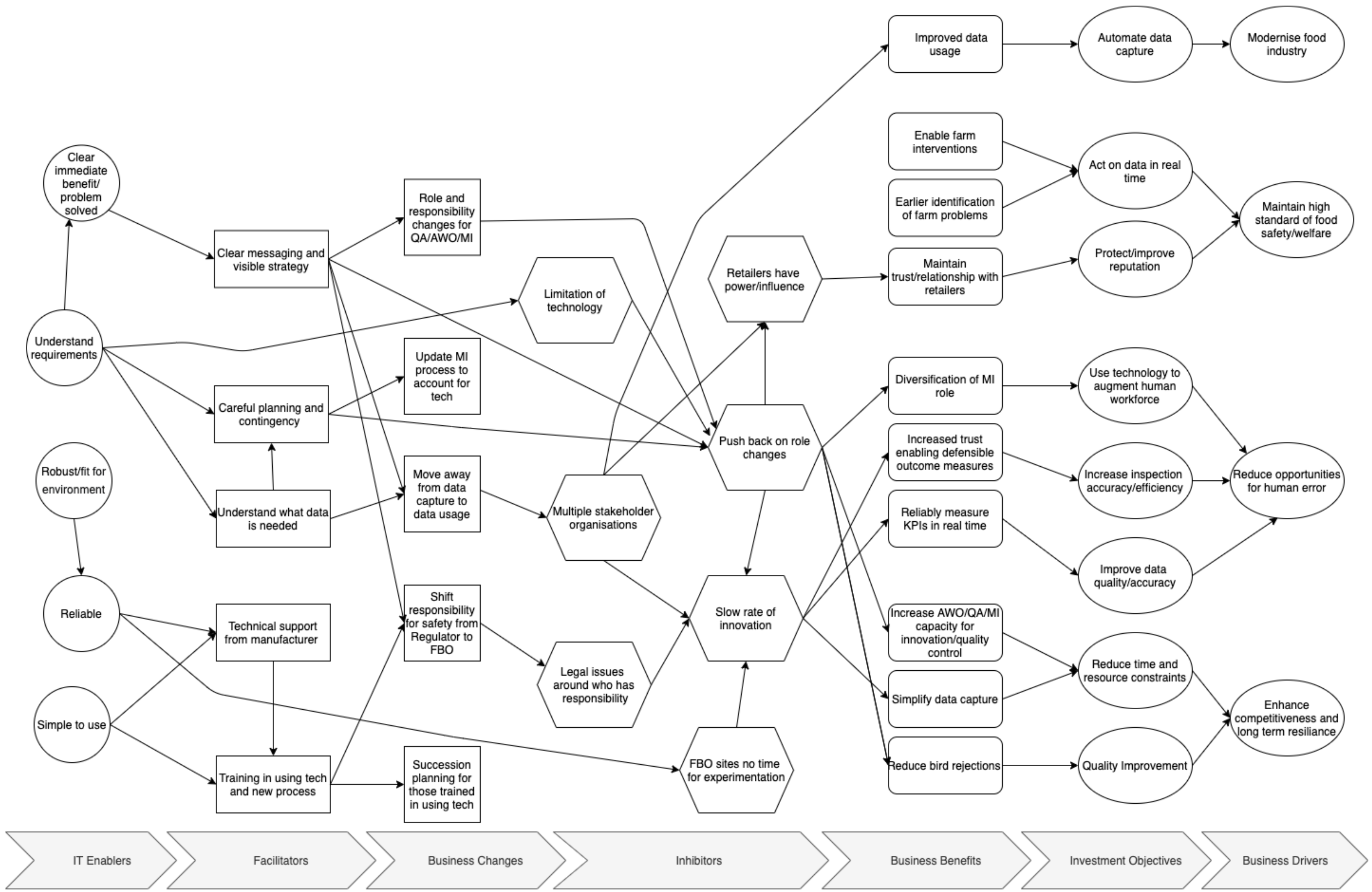



Figure 6: Benefits Dependency Network.

Third, it must be robust. In other words, the technology needs to be fit for the environment in which it is placed.  the plants within which these technologies are being installed have specific food safety concerns. Consequently, they are regularly cleaned using corrosive chemicals and large quantities of water. In addition, depending on where the technology is installed, there may be significant variations in environmental conditions such as humidity and temperature. This IT enabler feeds into the need for the technology to be reliable, as described above.

Fourth, the requirements must be well understood. Several considerations for the requirements of the system were highlighted, including:

- Compatible with existing systems across multiple stakeholders
- Compatibility with future systems
- Careful location of the technology, for example, should it be located before or after the inspector, or both?
- Whether automatic removal of the birds can be achieved
- How to manage variation within birds in terms of size and how they are presented on the line
- The design of the human-IT interface, for example, the inspector needs enough space to step back from the line to observe for issues and room to step towards the line to remove a bird. The technology cannot get in the way of this carefully choreographed movement.

The current process must be understood from both the inspector's and Food Co.'s perspective to fully appreciate the requirements and constraints within which the technology must seamlessly interface.

Fifth, the technology must demonstrate a clear benefit or solve an immediate problem. This is linked to the need to understand the requirements as just described. From a Regulator perspective, the benefit could be that technology in this capacity will promote safe food production, which in itself will provide consumers with greater confidence. For Food Co., the benefit would be the demonstration of the company taking more accountability for their product and providing more robust assurance to the Regulator and consumers alike. However, Food Co. operates in a highly competitive sector with extremely tight margins. This context is highly challenging for experimentation and innovation. In addition, to achieve buy-in from those on the ground using or interfacing with the technology, it must provide some benefit or solve an existing problem to be perceived as 'worth the cost'.

There is also the question of where the most significant benefit might come from solving different problems. Although from an external perspective, it may appear as though automating the identification of conditions could have the most significant impact, many other areas would benefit from modernisation.  the data capture method regarding rejections is currently done manually using clipboards and requires repeated data entry. From an MI’s perspective, it would be of significant benefit to use technology to improve this aspect of their job.  there are automated systems used in the red meat industry (namely pig production) where rejections are logged electronically (systems such as the Hellenic System). The Food Business Organisations (FBO) such as Food Co. typically own these types of systems, not the Regulator. There may be the possibility for this to be used in poultry plants but would require the FBO's implementation (Regulator employee 2). So, consideration must be given to whose problem is being solved and who is likely to be motivated to invest in solving that problem.

### 5.1.2 Facilitators

Facilitators are enabling changes to cover the support needed to roll-out the IT and achieve the change. These are one-off changes carried out during the roll-out process. First, it was clear that providing clear messaging and a visible strategy would be necessary to achieve the goal. In particular, consulting with the trade union from the outset and careful consideration of appropriate messaging to gain buy-in from MIs was highlighted.

It was noted by the MIs themselves that in the past, there had been several messages around changes to how meat inspection is carried out, many of which have failed to come to fruition. In many cases, there have been concerns around job security which has led to resistance and disengagement. As such, clear messaging and a visible strategy demonstrating how any changes will contribute towards the end goal and what the end goal is, is imperative.

Second, careful planning and contingency must be considered. Poultry processing plants operate under high pressure and high speeds, and each stage of the process is carefully choreographed. Even slight variations to this can cause significant knock-on effects throughout the system. Consequently, any changes must be carefully planned to minimise disruption to the day-to-day activities, especially during the roll-out phase. A trial is required to pilot new technology, plant selection should be considered based on potentially lower volume plants and/or the flexibility within plant systems. It was also noted that business-critical events might mean planned activities have to be cancelled at short notice. Therefore, contingency and backup plans must be in place for any trial or roll-out activity.

Third, training in using the technology and understanding any new process should be carried out to support the roll-out and adoption.  In the past, new technologies have been installed over the weekend, and front-line staff have been expected to get up to speed with how to use this on their own. In some cases, this has meant it has been difficult for front-line staff to troubleshoot issues and has undermined their trust in the results of the technology as there is little understanding of how it works.

Training would also need to be provided for Regulator staff. Although the Regulator staff do not need to know the full details of a Food Co.'s technological process, they need to understand the main steps. Further, for any Food Co. technology used by the Regulator, there would be a need for colleagues to be trained in its use.

Fourth, technical support from the technology manufacturer should be agreed on an ongoing basis to ensure users can troubleshoot issues as they occur in a timely fashion. This is in place for many of the systems already installed in the plant and, as such, is an established way of working. As already noted, any problems with the system can have significant repercussions, and stopping the line comes at a high cost, so it is essential that troubleshooting can be done quickly.

Fifth, an understanding of what data is needed should be reached. There are multiple stakeholders to consider, each with their own needs and priorities. From farmers to the Regulator and Food Co., there is a need to understand how data is accessed and used throughout the supply chain, where synergies might be achieved, and where unnecessary or unused data can be removed.

### 5.1.3 Business Changes

Business changes relate to how work needs to adapt to achieve the investment goals and use the new IT. Several business changes were suggested to implement the 21st Century Meat Inspector. The first was that updates to the inspection process would need to be made to account for any new technology. These changes would need to consider Safe Systems of Work and Health & Safety (Risk Assessments). The processes in place are carefully choreographed and controlled, as expected with a complex regulated production line. Changes to the inspection process, as well as knock-on effects to the rest of the line, must be carefully understood.

Along similar lines, there is a need to update the roles and responsibilities of several critical positions, including Quality Assurance (QA), Animal Welfare Officer (AWO), MI, and Plant Inspection Assistant (PIA). Each of these roles currently takes responsibility for some part of the inspection process and moving towards automated checks would change the nature of their position and the tasks they were required to carry out. It was noted that these changes could include freeing up more time for these individuals to do more than simply the essential tasks. Changes would likely need a lot of consultation and a clear vision of roles and responsibility from the industry and Regulator.

In addition, business processes must consider succession planning for those trained in using technology. There were examples given in interviews of other technologies which had been installed, with little consideration for those who would come to take responsibility for it. When the member of staff who knew how the technology worked moved to another site, there was a knowledge gap that caused issues when there were emergencies, such as a power cut that caused the systems to return to default settings.

A further consideration could be the organisation responsible for organising and delivering the training and the associated costs of training design and delivery. should this be provided by the software manufacturer, the FBO that has installed the software or the Regulator that use the software?

Linked to changes to the inspection process and updates to roles and responsibilities, there could be a shift in the responsibility for safety. Responsibilities are currently set out in legislation, and as a result, changes would need to be made across several stakeholders to adapt to new technology. Consideration must also be given to who 'owns' the technology from a financial point of view and how this might impact food safety and the provision of data.

There is also a need to move away from data capture and towards data usage to maximise the benefits of new technologies. One benefit identified from modern technology was the increased amount of data that could be captured. However, it was also acknowledged that existing data was not necessarily used productively. Without the appropriate structures to use and act on data captured, opportunities are lost, and data capture activities wasted. Businesses need to change from a mindset of capturing data 'because we can' to considering carefully how data might inform actions or answer pertinent business questions.

#### 5.1.4 Inhibitors

Participants identified seven inhibitors. First, the limitations of technology were a concern. Many of the MIs we spoke to described how, with experience, meat inspection became second nature. They explained how conditions would "come to you" rather than the inspector seeking them out. There was scepticism that this could be automated or that the human-technology interaction would be feasible.  having identification automated but physical removal carried out by a human.

Limitations of the technology also included the limited number of conditions being selected for automation, which would mean a human MI would need to remain on the line to identify other conditions, as well as the need for a human to physically remove birds from the line and place them into the appropriate category bin. Automating this part of the process could require the entire factory to be redesigned, which would be a significant investment.

Second, the multiple stakeholder organisations involved in the meat inspection process adds complexity that may inhibit changes to the process. The Regulator, FBO, retailers and consumers each have their own needs, concerns, and drivers. These do not necessarily align.

To achieve any change to the processes and legislation surrounding meat inspection, a systemic approach is required with collaboration across these stakeholders. Considering the financial pressures facing many FBOs, a clear business case would need to be put forward. For government bodies such as the Regulator, assurances on safety and reliability are paramount. For these reasons, the third inhibitor, the rate of innovation within this sector, is seen as particularly slow.

There were descriptions of existing processes within meat inspection that were far behind in terms of modern technology.  inspectors use five bar gates and scraps of paper to record rejections, manually entering this data into multiple other systems at the end of their shift. It is clear that if tasks such as this are yet to be modernised, steps to take meat inspection into the 21st century may be inhibited.

Fourth, it was commonly referenced that retailers have all the power and influence over how the FBO operates. Consequently, buy-in from FBOs may be limited if retailers are not bought in. Any proposed modernisation to the meat inspection process would need to provide sufficient assurance and/or benefit from the retailer's perspective.

Fifth, there are likely to be legal issues around who has responsibility for food safety, the technology, and the data. This is linked somewhat to the previously reported business change around who takes responsibility for food safety. In the current process, the MI is employed by the Regulator, and the responsibilities of the MI and OV are set out in legislation. As a result, any changes to these roles would require the legislation to be changed, which can be difficult and time-consuming to achieve. There are also considerations around who owns the data and how that data is reported. Even aspects of the process, such as how the data is stored and who has ultimate ownership of that data, would need to be considered and legislated.

Sixth, there is likely to be push back on role changes by those impacted, such as the MI and PIA. For some, there will be concern over job security, with a fear that by automating the detection of conditions, their skills and expertise will no longer be required. For others, it may be push back around learning new skills, such as how to interact with modern technology.

Finally, due to the nature of their business and the pressures of the production line, FBO sites have no time for experimentation, which could make the development of a suitable technological solution difficult. Studies have shown problems with solutions developed in the laboratory which are not capable of transitioning to industry. Without the ability to work with FBOs on-site to trial and experiment with potential solutions, this remains an inhibitor.

### 5.1.5 Business Benefits

Business benefits are how the IT investment will help to achieve the goal. Several business benefits were found concerning introducing new technology, such as AI, into the meat inspection process. Linked to the business change of moving away from data capture and towards data usage, business benefits would include improved data usage and reliable measurements in real-time.

It was evident from interviews that there are significant gaps in the current processes and existing systems that make data usage difficult.  many systems across different stakeholders (such as Food Co. and Regulator) are not integrated. In addition, the manual nature of the data input process means data is not entered onto these systems until the end of the day or even the following day. As a result, this data cannot be used in real-time to act on insights relating to incoming issues (for example, a farm load with hock burn).

If data capture were to be automated, this would have the additional benefit of simplifying data capture. Currently, multiple individuals are involved in capturing and inputting data into various systems, which increases the chance of human error. Simplifying this would be a significant benefit.

New technology could also enable farm interventions by improving the access and usage of data. The FBO needs to provide reliable and timely data back to farms to allow interventions once flock issues have been identified.  if a farm has a problem with excessive hock burning, which can only be seen after de-feathering, this is likely to affect the whole flock and requires action to be taken at the farm. Sharing data with the farm may also mean less impact on food production at the FBO and help promote the quality of the product being produced.

Improved technology would provide the business benefit of providing fast and reliable evidence of issues such as this, which can be easily relayed back to the farm. This, in turn, will enable earlier identification of issues. The later issues are found, the more this costs the Food Co. and the farm. When a flock are found to have issues, this is docked off the payment made back to the farm. In many cases, these birds cannot be used as intended, which leads to a supply issue for the Food Co. To mitigate the risk of this, the Food Co. may overstock, which can be costly. If issues can be identified earlier and interventions made sooner, this could improve the supply chain and reduce losses at both the farm and Food Co.

An added benefit related to farm interventions is providing more defensible outcome measures (trust data). Tensions were reported between the Regulator, Food Co., and farms regarding being able to defend the outcome measures (reports on rejections and conditions). Given the cost to farmers of having birds reported with issues, they will challenge the reporting process.

Where technology can be used to improve the accuracy of inspection and provide the evidence to back up reports of issues ( photos and an audit trail of the farm, house and load), this can move the conversation away from the accuracy of the data and towards improving the conditions on the farm.

In addition, automation of the inspection process may reduce rejections by reducing human error where healthy birds are incorrectly rejected or by reducing the instances of retailers rejecting products later down the line where poor quality birds have been missed. The former results in fines for farmers, the latter in fines to Food Co. from retailers. Any improvement to the accuracy of inspection will save time and money and increase assurances for regulators that any food safety issues are reliably identified.

Another potential benefit to come from the use of new technology is to maintain trust/relationship with retailers. For Food Co., this is paramount. Retailers are highly concerned with ensuring food safety and food quality is maintained at their suppliers to avoid scandal and reputational damage. Any assurance or improved reliability of data that can be achieved through the use of new technologies improves this relationship. For Food Co., their reputation and relationship with their retailers is one of their most pressing concerns.

The final benefits to be identified are the diversification of the MI role and freeing up AWO/QA/MI to be more proactive. There are significant time and resource constraints in the current system, which means that each role is at capacity simply doing those activities, which are essential from a legislative and food safety perspective. There is very little time for proactive activities, which might improve the system long term. If some of the activities carried out by these individuals could be automated, this would provide the opportunity for their roles to be diversified, and allow them more time to be proactive, carrying out activities which the business would *like* to do, but at present does not have the capacity for. This might include time for innovation and increased quality control. The MI may take more of an auditing focus across FBOs rather than carry out the inspection directly to ensure standards are being met and the technology is reliable.

#### 5.1.6 Investment Objectives

Investment objectives, in this context, are the goals associated with an IT investment. Many of these have already been touched upon through earlier sections, and as such, they will be recapped here. Others are more independent and will be described in more detail.

By adopting new technologies, such as AI, the FBO and the Regulator aim to automate data capture, which will improve data quality/accuracy, increase inspection accuracy/efficiency and reduce time and resource constraints. They will also seek to act on data in real-time. Each of the benefits associated with these goals has been described in more detail in the previous sections.

There is also the goal of protecting or improving reputation, which, as has already been described, is a crucial concern for FBOs. Any technology which can provide additional assurances on food safety and quality goes towards reputational protection and increasing trust within the supply chain.

The introduction of AI and automation would also augment the existing workforce, which require holiday and sickness provisions. This is particularly apparent in the current COVID19 crisis. Technology can be used in place of humans or enable human interaction off-site (such as remote access). This would create flexibility in the workforce and improve the consistency with which standard tasks are carried out.

The final investment objective is to see quality improvements. Providing high-quality products ensures the FBO's reputation is upheld and that its relationship with customers is maintained. Both of these ultimately feed into reducing costs and maximising profit, as if the retailer rejects products due to poor quality, the FBO pays a fine. If an FBO's reputation is damaged, this can mean the loss of customers. Consequently, quality improvements are a significant investment objective for adopting technology in the meat inspection process.

#### 5.1.7 Business Drivers

Through this discussion of the IT enablers, Facilitators, Changes, Inhibitors, Benefits and Investment Objectives of applying new technology to meat inspection, we have identified three primary drivers.

First, a need to modernise the food industry to remain progressive, competitive and resilient, and second, delivering exceptional standards of food safety/welfare are drivers for adopting new technology. This is an industry that could benefit greatly from taking advantage of modern technological innovations. The Regulator is keen to make the most of the additional food safety assurances which come with automation and AI, which is why they have begun a digital transformation. Although the UK has an excellent reputation for food safety and animal welfare, it was noted that in Europe, FBOs generally have a higher level of modernisation when compared to the UK. To compete in a global market, the UK must invest in innovation to promote food, public and animal safety.  Food safety is a concern shared across all stakeholders, from the consumer through to the farmer, with the knock-on effects on reputation, cost, and trust.

Third, there is a drive to reduce inspection subjectivity. Given the nature of inspection, the variation in inspectors' experience, and the variance in the look of the birds being inspected, adds subjectivity to the task. This subjectivity may cause issues across shifts and sites and reduce the trust in data accuracy based on these assessments.

## 5.2 WP2 Post-Mortem Inspection

### 5.2.1 Deep Learning for PMI

The classification results from ResNet-18 for all three batches of images can be seen in Figures 7-9. The overall model classification accuracy was best for the third batch with a value of ~90%. The lowest classification accuracy was batch 1 which was most likely due to the lower number of images available in this batch to train the models. For all three models the biggest errors were the wrong classification of normal images as dark/red. This result would lead to acceptable carcasses being classified as unacceptable, although as the technology is anticipated to be a pre-screening step this would be acceptable and preferable to the method classifying dark/red images as normal. In addition to the overall accuracy, there were two other criteria used to judge the models and both can be calculated from the confusion matrix. The first is recall which is the class-wise correctly identified samples, i.e., green cells, divided by the total samples in the row. The second criterion is the precision which is the class-wise truly identified samples, i.e., green cells, divided by the total samples in the column.

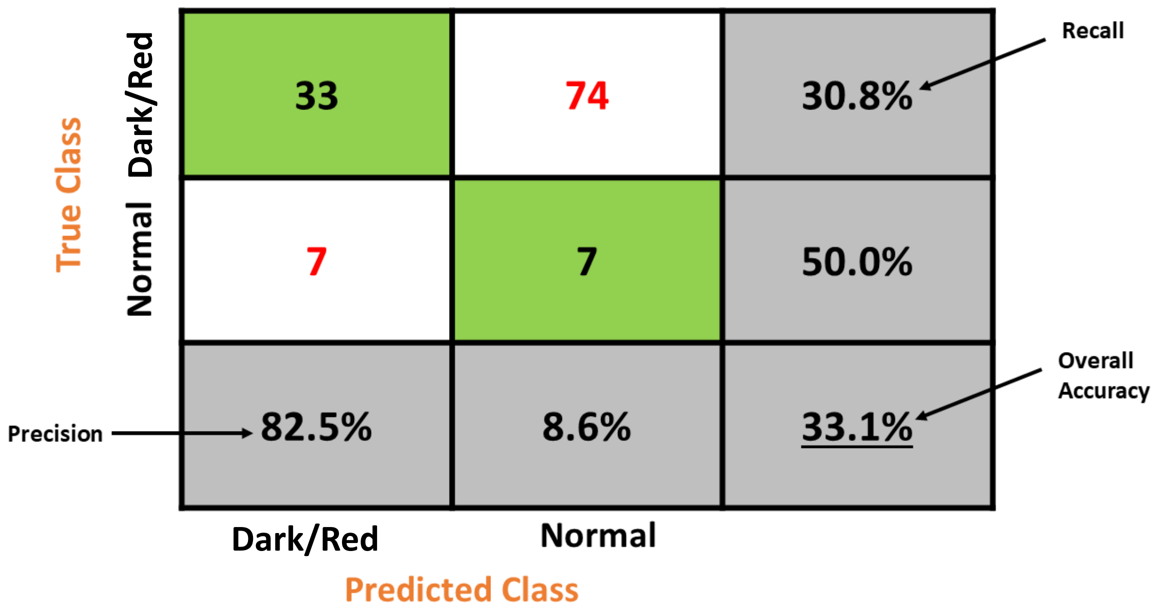



Figure 7: ResNet-18 batch 1 classification results.

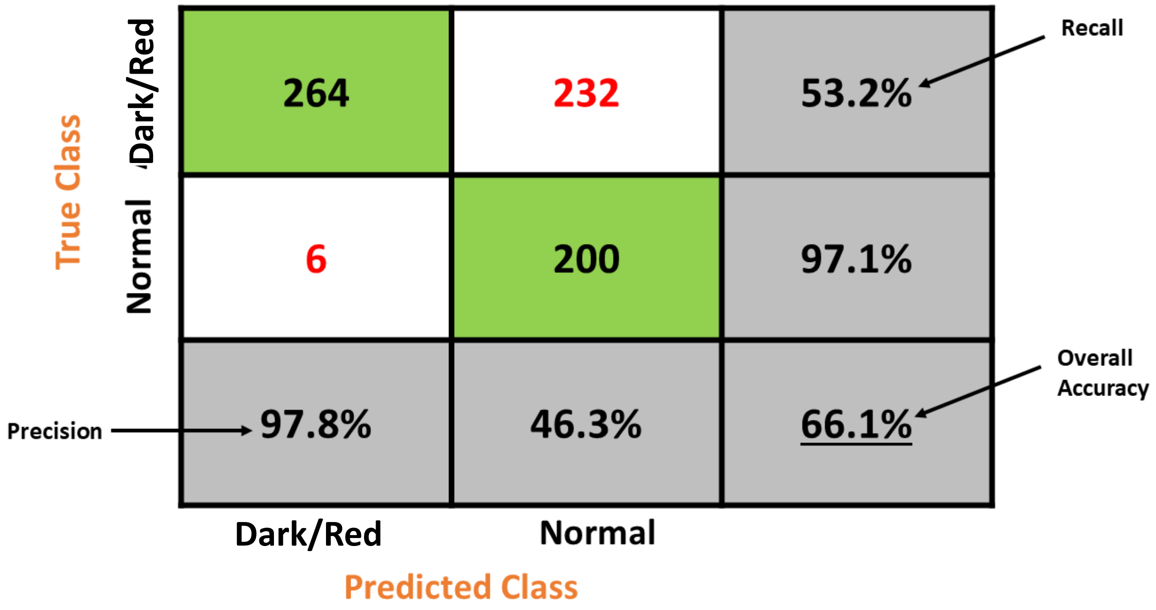



Figure 8: ResNet-18 Batch 2 classification results.

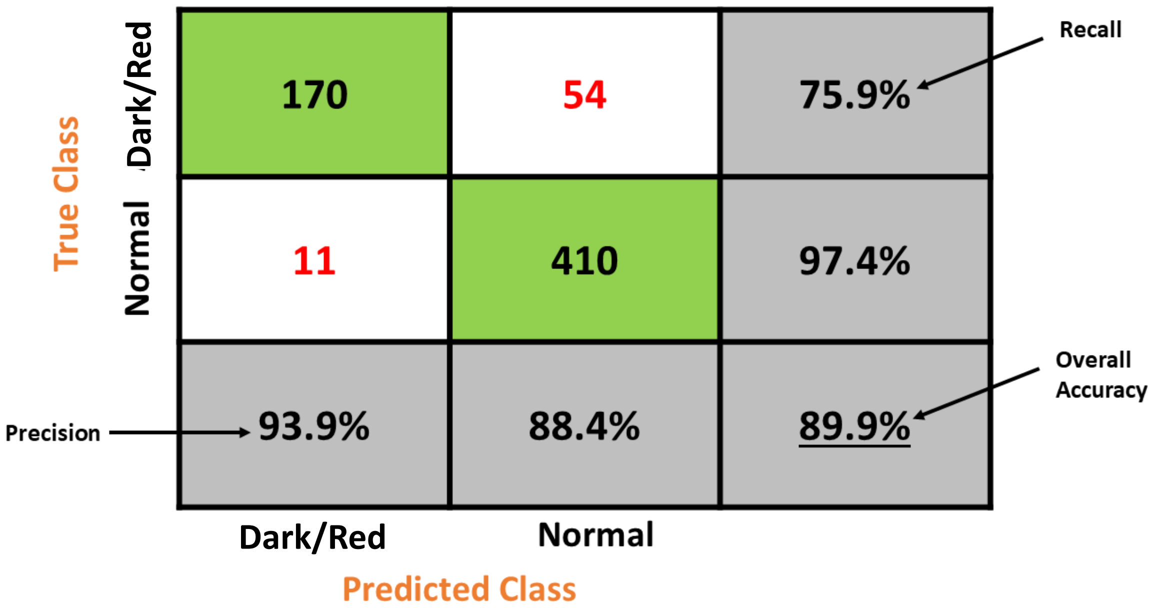



Figure 9: ResNet-18 batch 3 classification results.

Figures 10-12 present the classification results from the AlexNet model. These followed the same general trend that batch 1 had the lowest classification accuracy and batch 3 had the highest classification accuracy and the majority of the incorrect classifications were normal carcasses classified as dark/red. In general, the AlexNet results were slightly lower than the ResNet-18 results for all three batches. The reason for such a result is that it is known that the deeper the CNN is, the higher the accuracy, and the less the possibility of overfitting[30]. The main limitation with this part of the work is that all images were recorded once the PMI had been performed so the manual labelling of data was performed by University of Nottingham researchers who are non-poultry experts and were classifying images as abnormal based on marginal differences in skin colour. It is envisaged that if the images were collected in a consistent manner during the actual PMI there would be a much greater difference between the abnormal and normal carcasses and the models would achieve a much higher accuracy. In addition, recording images whilst PMI was performed by a meat inspector would enable more accurate labelling of the images as the meat inspectors are trained to identify all conditions and have experience and expertise lacking in the University of Nottingham researchers. If it would not be feasible to have a meat inspector label all images unsupervised and semi-supervised machine learning approaches call also be explored.

It is still nevertheless envisioned that in the first instance, the imaging and classification could act as an initial screen to identify carcasses where a condition may be present and that these could be highlighted to a meat inspector for a more detailed inspection and decision. This screening would aid MI screening, allowing them to spend more time inspecting carcasses suspected to have a condition.

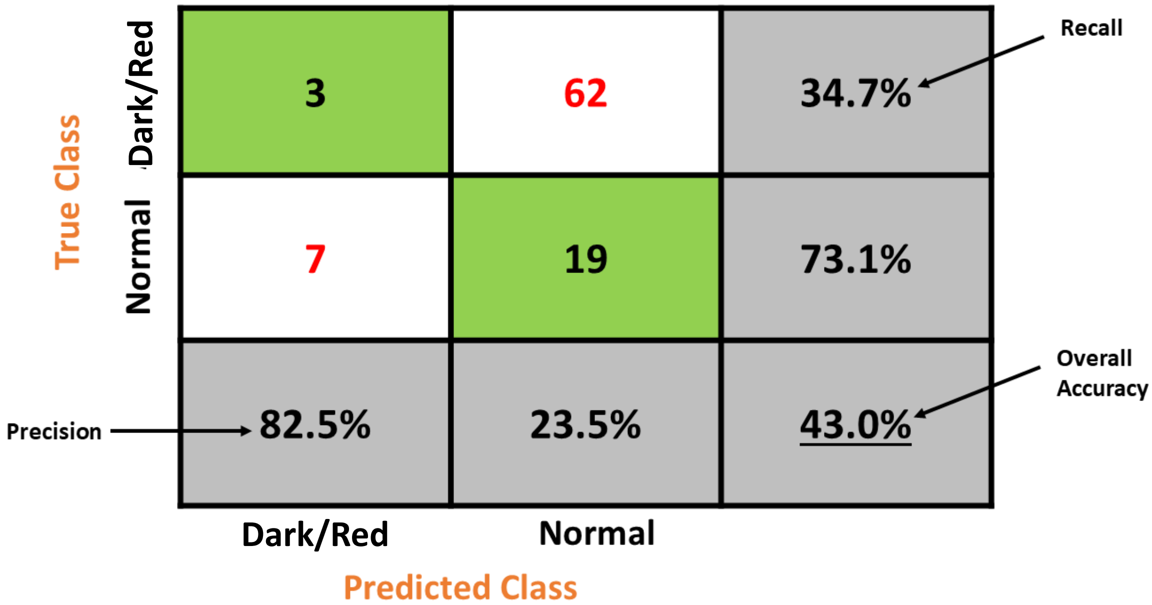



Figure 10: AlexNet batch 1 classification results.

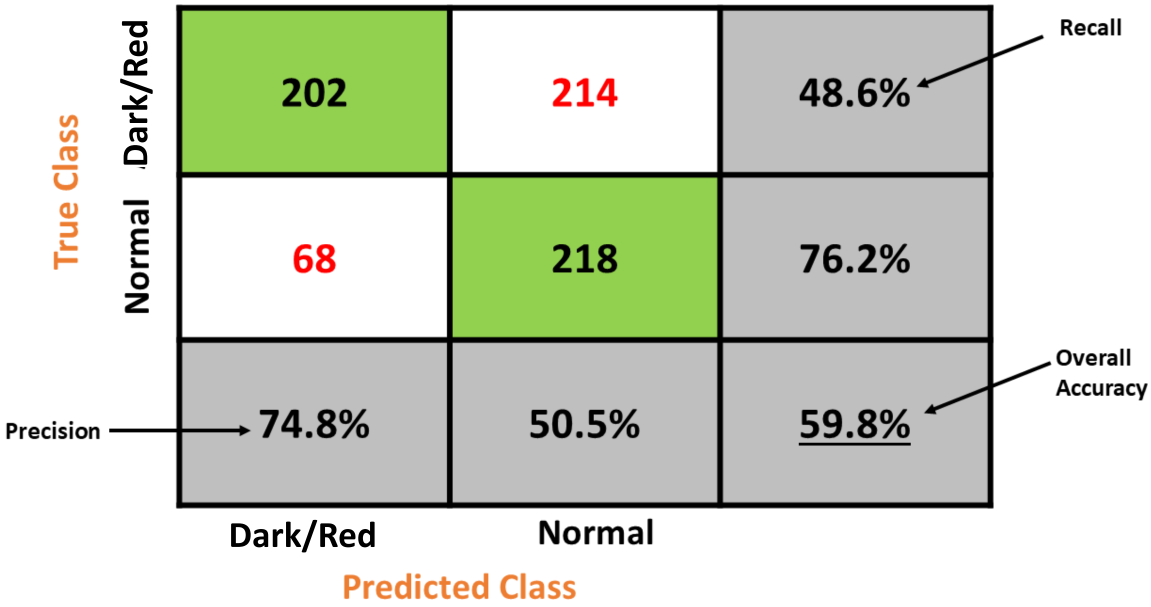



Figure 11: AlexNet batch 2 classification results.

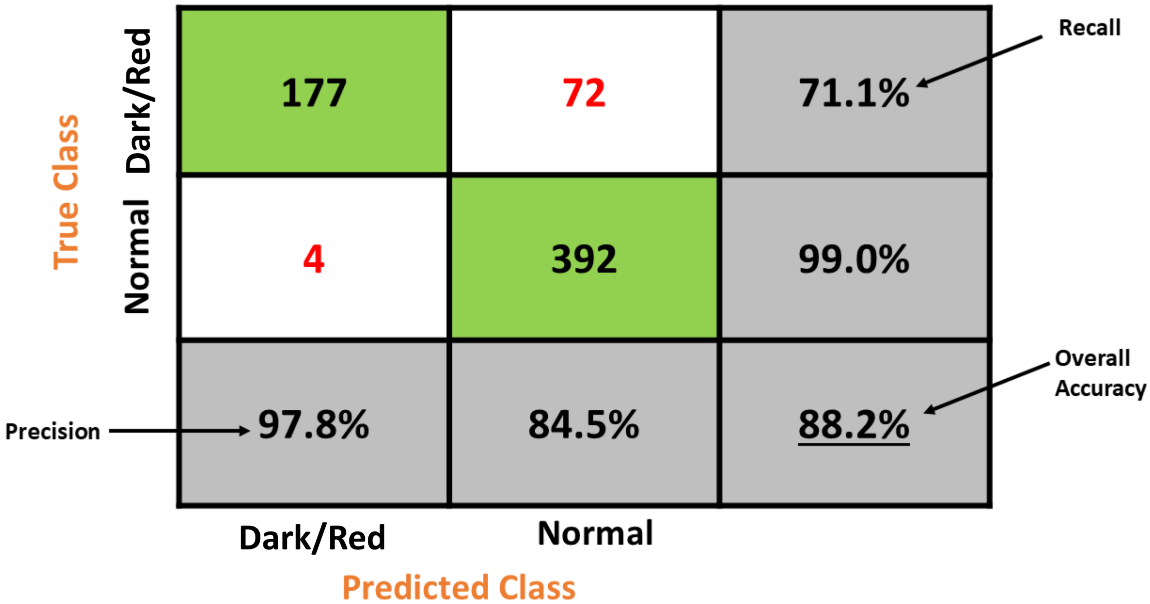



Figure 12: AlexNet batch 3 classification results.

### 5.2.2 Quality inspection X-ray

Results were analysed via clustering the recorded XRD profiles. As with all clustering, the motivation was to group together similar observations while separating dissimilar observations and in this case to attempt to find natural grouping of material quality. A first-derivative pretreatment of the profiles was applied as a pre-processing step as this was found to give greater contrast between the XRD profiles than using the raw data without pre-processing. The results of pre-processing the XRD profiles for a random selection of breast tissue measurements are shown in Figure 13.

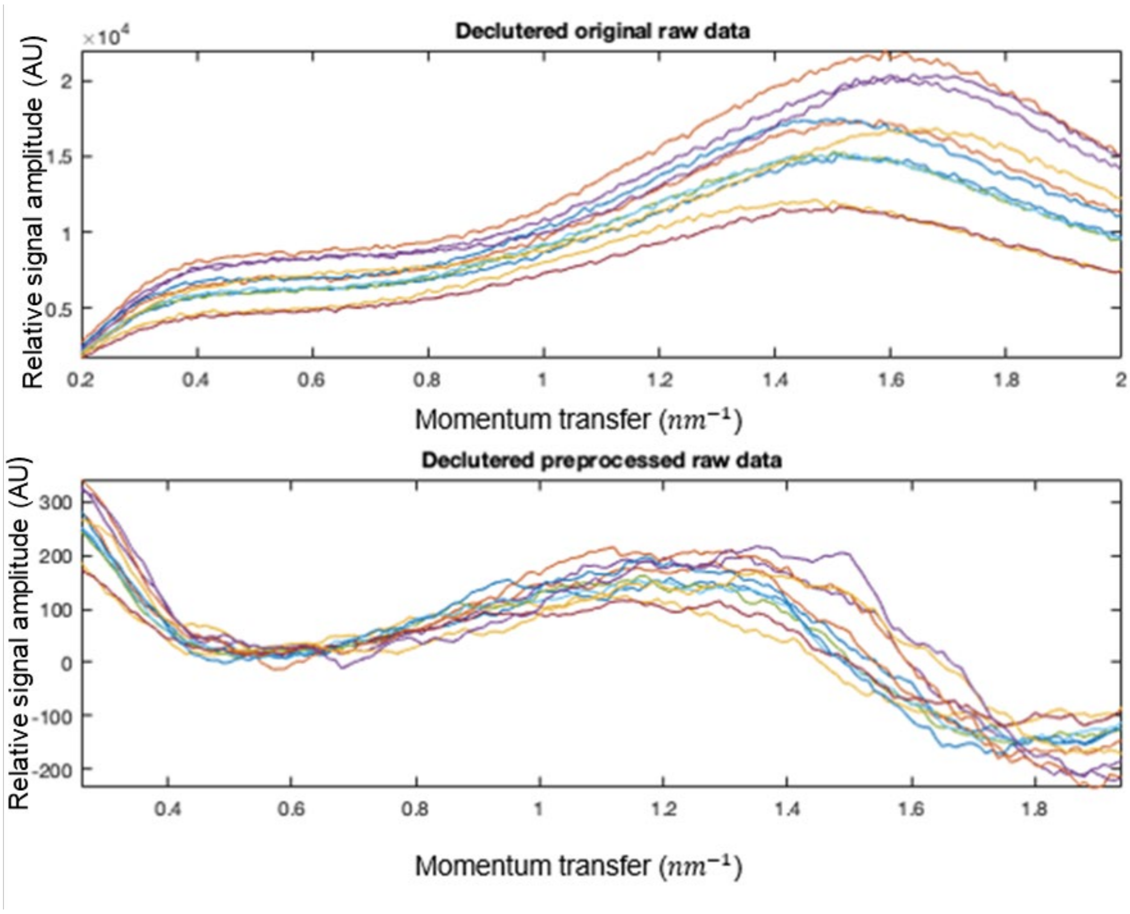
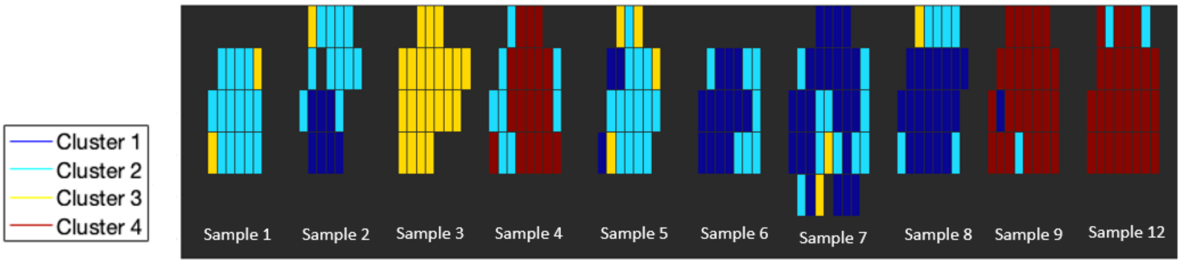



Figure 13: A random sample of 10 XRD measurements from a set of 10 chicken samples (above) with the processed profiles (below).

The processed profiles were then clustered using the K-means clustering algorithm using four clusters, the results of which are shown in Figure 14. As can be seen, the clustering segments the images spatially, rather than apparent random assignment of pixels to clusters, indicating that meaningful patterns in the data are being extracted. The cluster centroids in Figure 14 show the mean profiles of each of the four clusters. This analysis stops short of determining the meaning of the clusters but indicates spatially dependent information, potentially relevant to the material composition and quality of the samples, could be derived from X-ray diffraction.

The cluster analysis does not know anything about the ground truth of the specimens. It only serves to place the XRD spectra into groups with spectra that are similar. The physical meaning of these groups cannot be determined without further analysis. Typically, this would involve having spectra measured for all the different types of tissue (for example, normal muscle, connective tissues, fat, woody breast, etc.) against which the cluster can be compared and/or be used to enforce some boundary conditions on the analysis.

Despite not being able to say “cluster 1 means muscle with woody breast” (and so on), what we can say, is that the clusters seems to be spatially correlated. If they were meaningless, then we might expect the clusters (or at least the spectra’s assignment to a particular cluster) to be randomly distributed across all samples. This isn’t the case here. The origin of the spatial correlation is unclear at this stage. As well as betting potentially correlated with meat condition, it may also have influence from properties like sample attenuation and water content, which are not related to meat condition/quality.



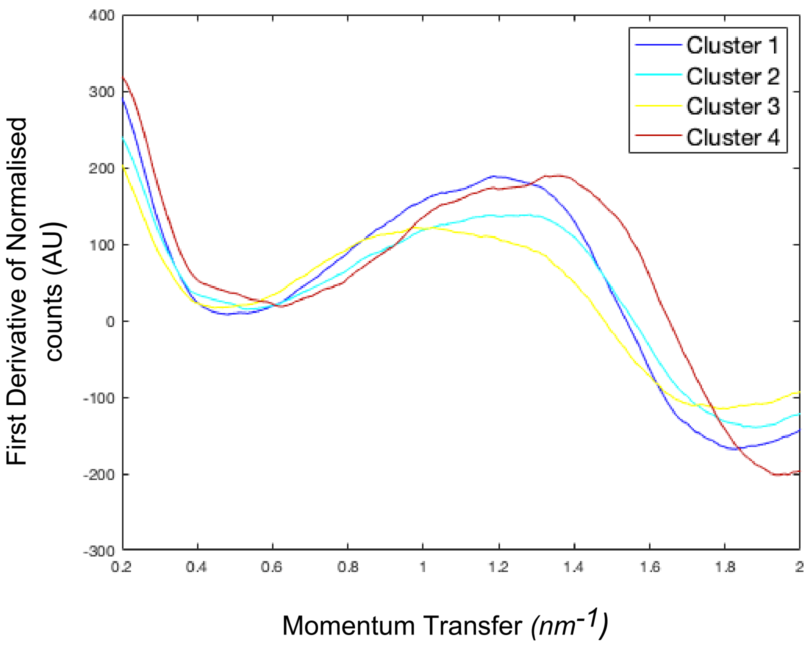



Figure 14: K-means clustering of diffraction data that has been pre-processed using first derivative smoothing (top sub figure). The 10 chicken breast samples (1-4 = normal, 5-8 = white stripe, 12 = woody breast) have each measurement position clustered to one of four clusters. The corresponding centroid profile of each cluster is shown in the lower sub figure.

We have carried out some preliminary measurements using a limited number of samples to investigate the efficacy of X-ray imaging and diffraction to be able to distinguish between normal chicken fillets and those affected by wooden breast syndrome.

Results suggest that 3D X-ray imaging (CT) can identify a variation based on the macroscopic ‘texture’ present in the image.  X-ray diffraction (XRD) is able to provide a material specific output but in this case, it has not been possible to definitively say whether there is a consistent and identifiable feature that can be used as a discriminator.  This is mainly related to having a limited number of samples and the need to build in constraints on the analysis processes.

Further effort is required here to really understand the potential of both X-ray modalities.  A larger number of samples will enable statistically relevant conclusions to be drawn.  Automated classification of image texture could be a significant metric to assist in meat grading/quality assessment. We believe that machine learning approaches, in which labeled data sets of chicken samples can be modelled according to their composition and CT and XRD profiles, in addition to domain expertise driven modelling where knowledge of X-ray CT, XRD and the context could aid sample classification using non-destructive testing. The former approach would require a larger data set, whereas the latter approach could achieve more with less data but with constraints added to derive accurate solutions. Commercial online X-ray CT technologies do exist, but the research team identified no example of work in the area of poultry inspection. In addition, the cost of these technologies is considerably higher than common optical imaging system, which is a larger barrier for wider adoption by the sector.

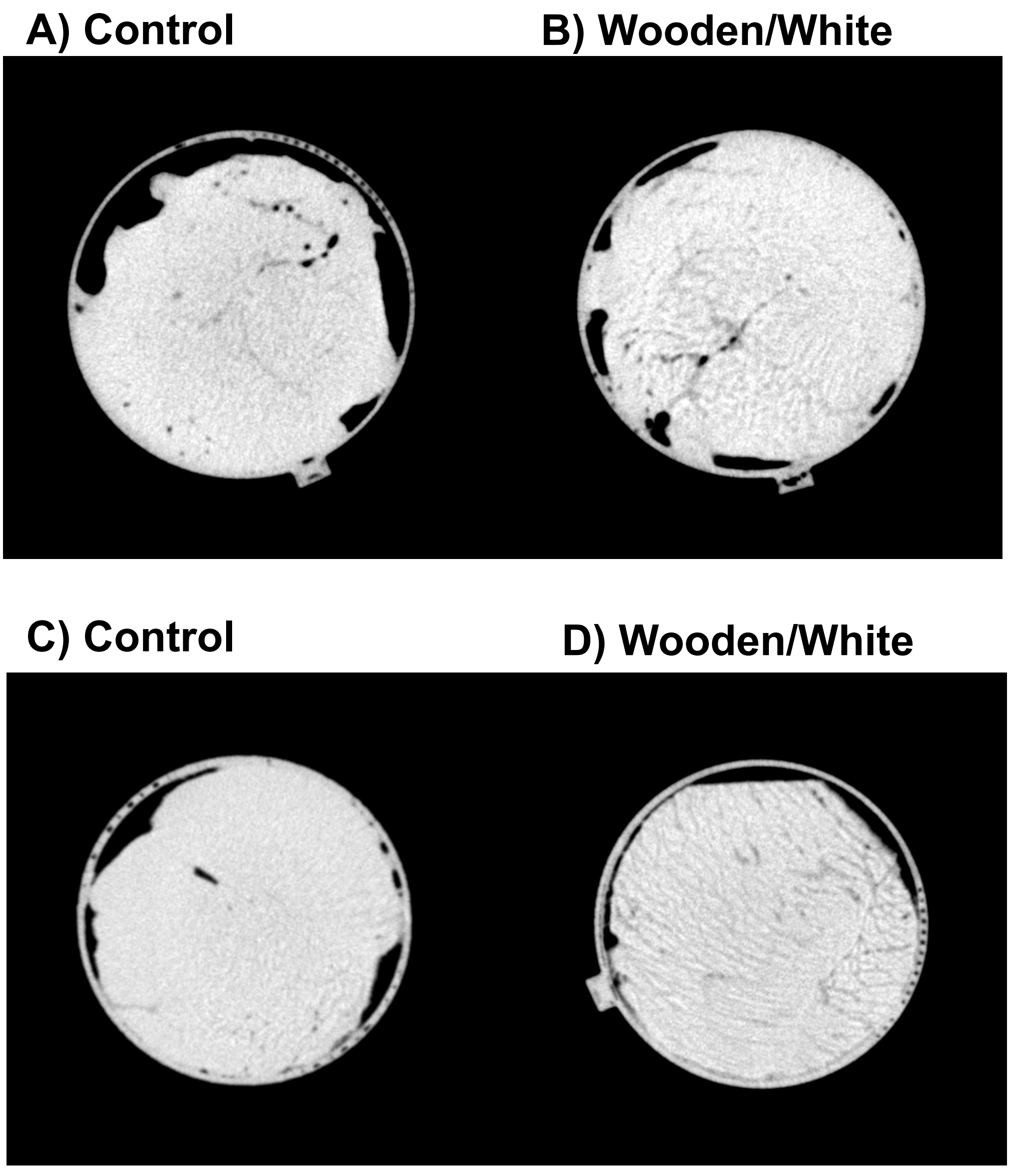


Figure 15: X-ray results on different chicken breast samples. A and C) Controls, B and D) wooden breast or white stripe.

### 5.2.3 Quality inspection hyperspectral

Figure 16 displays the hyperspectral image results on the whole chicken breast samples. Thin white stripes are more visible on the centre and right images which are breast samples containing wooden breast and white stripe respectively. Figure 17 displays the spectra (averaged over all image pixels) for the three different breast samples and a clear increase in relative reflectance was observed for the sample containing white stripe. This was most noticeable between the wavelengths of 900 and 1400 nm. This could be a result of the firmer tissue in the sample with wooden breast creating a strong reflection of light and highlights the potential of hyperspectral imaging to detect wooden breast in acute cases where visual inspection is not capable.

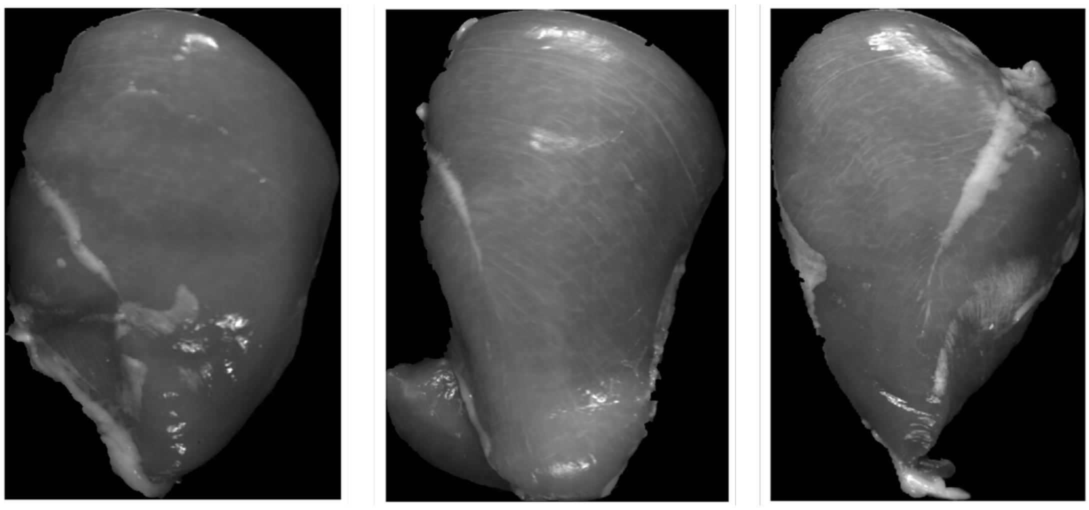


Figure 16: Chicken breast samples. Left) control, Middle) wooden breast, Right) white stripe.

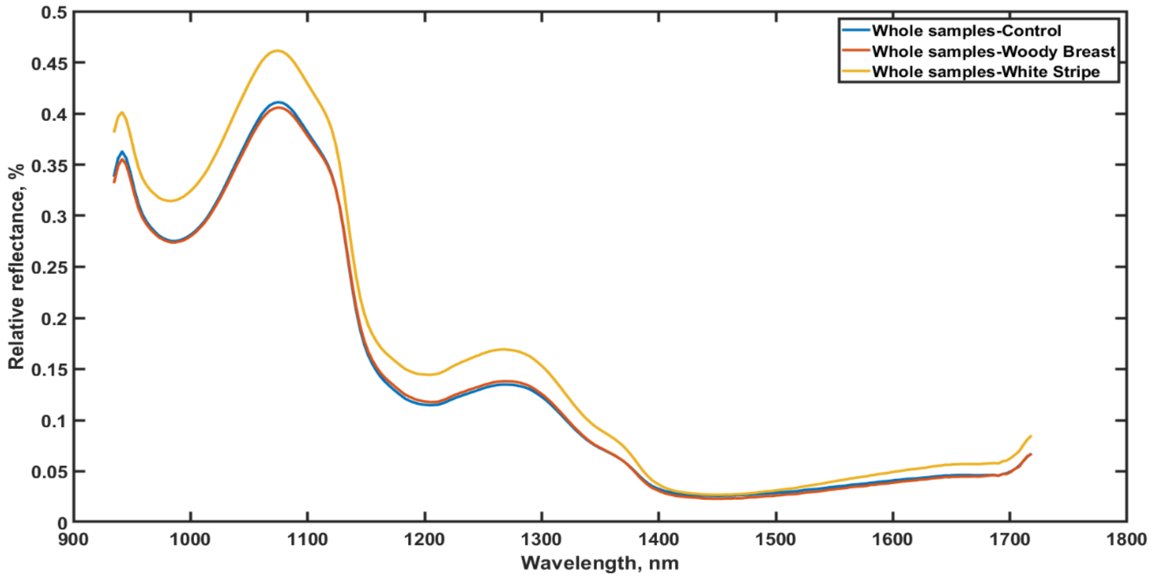



Figure 17: Recorded spectra from whole chicken breast samples.

Hyperspectral imaging on chopped chicken breast samples (Figures 18 and Figure 19) showed the same results as the whole breast samples which is that thin white stripes/line are more noticeable in the samples with wooden breast or white stripe and the relative reflectance was higher in the samples with wooden breast.

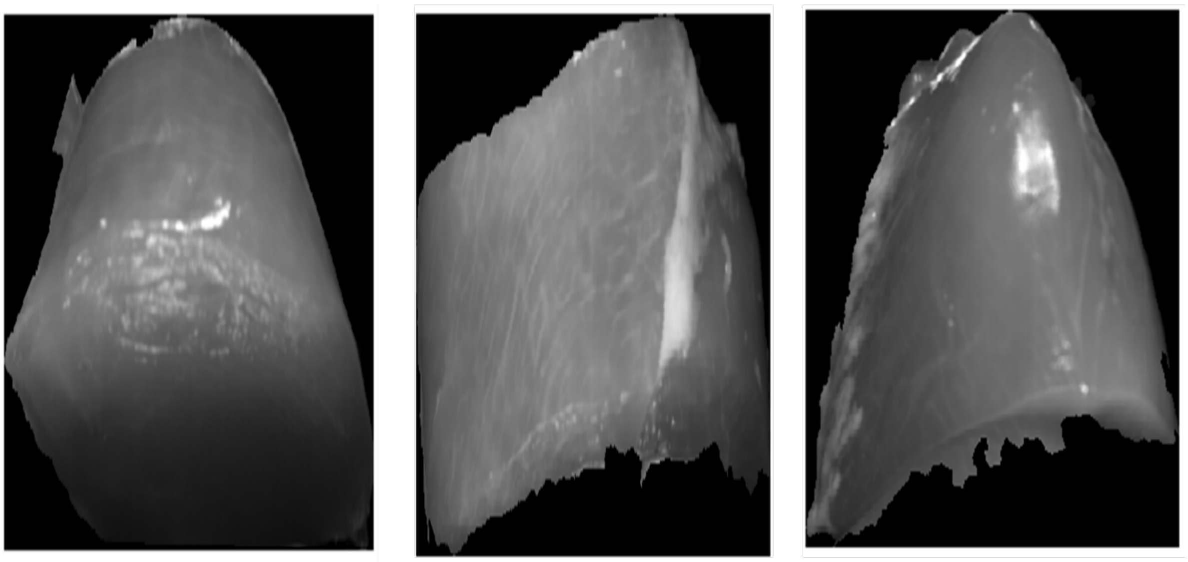


Figure 18: Chopped samples: Left) control, Middle) wooden breast, Right) white stripe.

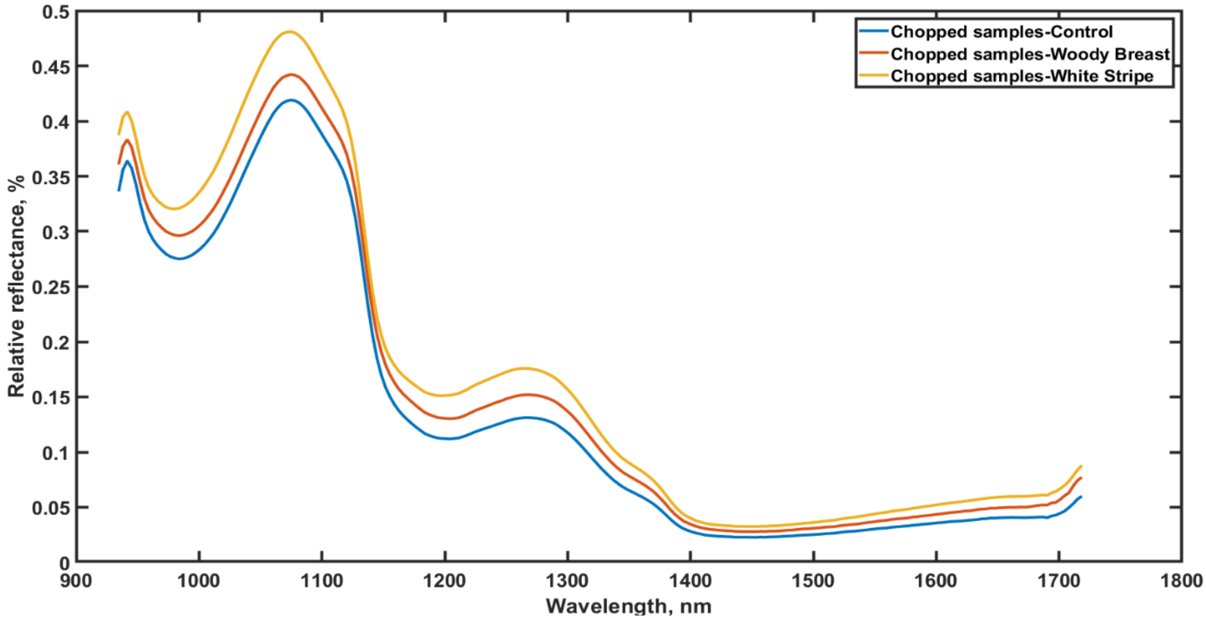



Figure 19: Recorded spectra from the chopped samples.

Several studies exist in the literature where optical sensors operating in the NIR range were utilised to detect and study wooden breast or white stripe in chicken.

Hyperspectral imaging was used to differentiate between healthy and wooden chicken breast fillets in the NIR range (760-1040 nm) in an online scheme[31]. The study was accomplished via a commercial online system (QVision500, TOMRA Sorting Solutions, Leuven, Belgium) and was also used to determine protein, moisture, fat, pH, and colour (L*,a*, b*). A Partial Least Square Discriminant Analysis (PLSDA) classifier achieved an overall classification of 99.5% with all 28 wooden breast samples identified. The correlation coefficient (r) values for protein, and moisture were 76%, and 67%.

Another study implemented the NIR sensing technology (760-1040 nm) and a nuclear magnetic resonance (NMR) relaxation system[32]. While the whole breasts were used for NIR measurements, a cylindrical sample with 8 mm height, and 20 mm diameter was used for NMR measurements, similar to the X-ray work in our current project. Linear Discriminant Analysis classification models revealed that the overall classification accuracy of wooden breasts vs. healthy samples was identified with a success rate of 68.7%-96.1% using NIR and 76.9-98% using NMR.

Colour vision and NIR spectroscopy (1150-2150 nm) were investigated to classify wooden breast and differentiate them from normal chicken breasts[33]. Intensity and texture features were extracted from colour images and reflectance spectra were extracted from the NIR system. Several classifiers were utilised to differentiate between defected and healthy samples. Such classifiers included support vector machines, multilayer perceptron, random forest, and decision trees and the highest accuracy obtained from the vision system was 91.8%, whereas the value was 97.5% from NIR sensor.

White stripe was evaluated in chicken breasts using Visible/NIR hyperspectral imaging (400-1000 nm)[34]. Principal Component Analysis (PCA) was used to select the most influential wavelengths including 450, 492, 541, 581, 629, 869, and 980 nm. Texture and histogram features were extracted and PLSDA was implemented for classification which results in classification accuracies using all, and selected wavelengths being as high as 95.8%, and 91.7%, respectively.

Visible/NIR spectroscopy (200-1100 nm) was also used to quantify the presence of white stripe in turkey breast samples based on different quality traits such as L*a*b* colour components, pH, drip loss, cooking loss, moisture content, protein, and ash content[35]. White stripe samples were divided into moderate that has striations thickness of less than 1 mm, and severe with a thickness higher than 1 mm. Statistical analysis showed no significant difference between the mean of each of the previous traits although the fat content of normal samples was less that for medium or severe white stripe samples.

The previous work demonstrated the potential of the techniques and was more comprehensive than the feasibility work, performed on a limited number of samples, in this current work. Previous work has even demonstrated the potential to identify wooden breast online. The majority of these previous works utilised different supervised data fitting (for example, machine learning) methods which require the labelling of samples with and without known conditions and is often a barrier for widespread adoption of the technologies in industry. To address this challenge other machine learning methods such as semi-supervised, active and transfer learning can be explored.

# 6. Recommendations for Future Work

This project assessed the feasibility of using sensor technologies and advanced data analytics for poultry inspection. The project focused on PMI and tested a range of different sensing technologies at Food Co. and in the laboratory. The project also investigated the use of sensors to detect quality issues within poultry and utilise expertise from the Hartree Centre for advanced image and data analysis. To determine the requirements and benefits of any proposed new technologies, the study provided a benefits realisation model derived from stakeholder engagement through interviews. The benefits management modelling focused mainly on PMI detection, although it is likely that many aspects of the model would apply to other areas.

The findings indicate that the application of AI, sensor and data analytic technologies provide the opportunity for the realisation of a considerable range of business benefits that would be valuable for the Regulator (for example, increased safety standards for food production improving consumer safety), MIs (for example, enriched work activities maximising best use of specialist knowledge), FBO (for example, real-time data-informed decision making), and farms (for example, earlier information on animal welfare issues). However, to realise these benefits, there would likely need to be programmes of organisational change in terms of process and job redesign combined with investments in the design and development of AI, sensor, and data analytic technologies.

The benefits mentioned above reflect both tangible and non-tangible enhancements and should be complemented by an economic cost-benefit assessment and qualitative indicators of benefits. Including these measures would be important to enable effective management and monitoring of benefits delivery throughout transformation projects.

Further, AI, sensor and data analytic technologies would need to be thoroughly tested before implementation to minimise disruption to the FBO. Designing replication of the FBO production line for testing is a significant challenge. The multiple stakeholders involved in the food production process provide a complex environment. They may present challenges for achieving agreed standards for data access, data governance, responsibility and liability for automated decisions, and committing financial resources.

Deep learning image processing demonstrated some potential to identify carcasses with known conditions although the primary limitation of the work was that all images used were down stream of the PMI and all carcasses of concern would have been removed. However, the machine learning models on the larger batches were able to identify carcasses with either dark and red skin and it is assumed would perform better with poultry conditions which are visibly more noticeable. To fully assess the potential of these techniques image analysis should be performed during the PMI and would be the logical next step for the research to continue.

Further effort is required to fully understand the potential of both X-ray modalities and hyperspectral imaging for detection of quality issues in chicken breasts. Future work should focus on utilising a larger number of samples, exploring the potential of multi-sensor fusion activities and addressing the technical and economic barriers in developing systems that can operate effectively in production environments. The majority of work available in the literature is currently within technology readiness level (TRL) 1-4 and larger pilot scales with industry partners are required.

Focus areas to continue the work:

- Image collection during post-mortem inspection at a poultry facility
- Infrared imaging at poultry facility for DOA component of the project
- Large scale laboratory and pilot scale study with X-ray and hyperspectral systems for quality issues such as wooden breast and white stripe
- Design of effective business strategies for Human + AI augmented meat inspection in complex stakeholder environments
- Novel production line testing environments (for example, Digital Twin) for AI enabled meat inspection

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