MACHINE LEARNING BASED AFP INSPECTION: A TOOL FOR CHARACTERIZATION AND INTEGRATION

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ABSTRACT

Automated Fiber Placement (AFP) has become a standard manufacturing technique in the creation of large scale composite structures due to its high production rates. However, the associated rapid layup that accompanies AFP manufacturing has a tendency to induce defects. We forward an inspection system that utilizes machine learning (ML) algorithms to locate and characterize defects from profilometry scans coupled with a data storage system and a user interface (UI) that allows for informed manufacturing. A Keyence LJ-7080 blue light profilometer is used for fast 2D height profiling. After scans are collected, they are process by ML algorithms, displayed to an operator through the UI, and stored in a database. The overall goal of the inspection system is to add an additional tool for AFP manufacturing. Traditional AFP inspection is done manually adding to manufacturing time and being subject to inspector errors or fatigue. For large parts, the inspection process can be cumbersome. The proposed inspection system has the capability of accelerating this process while still keeping a human inspector integrated and in control. This allows for the rapid capability of the automated inspection software and the robustness of a human checking for defects that the system either missed or misclassified.

1. INTRODUCTION

1.1 Purpose

The advent and popularization of AFP manufacturing in the aerospace industry has led to large jumps in the size and throughput of various composite structures that are realistically possible in a traditional manufacturing setting. This increase in the speed of material deposition, however, has a number of notable drawbacks. Principally among them, automation with robotic components leads inevitably to a lack of control in the quality of what is produced on a system. The result is potential for the rapid production of defects in manufacturing and thus a need to detect, identify, and characterize defects. A collection of common AFP defects can be found in [1]. Traditionally, this has been accomplished through the use of human inspectors, and thus the inspection time and quality are subject to human variations. The need for human inspectors also placed an additional restraint on the availability of experts needed to accomplish the task. In recent years, the concept of automated inspection systems coupled with automated manufacturing systems has generated a great deal of interest in the both the academic and professional communities. Combined with the advancements in machine learning techniques automated inspection has the potential to reduce inspection time and cost and increase consistency while having high accuracy. Reliable rapid inspection also allows for an additional data source that can be accessed for further study. This enables advances in product lifecycle management (PLM), the development of a digital twin, and the post-manufacturing analysis of a particular structure [2].

1.2 Proposed Solution

In previous work we extensively discuss the architecture of the network used for defect recognition, and the process by which the defects are classified [1]. In this publication, we intend to outline the most recent additions to the system which now incorporates a UI for the USC developed Machine Learning tool, as well as an AFP defects MySQL database that can be shared with other projects. The paper is going to be divided into the following sections: Section 2 will discuss the literature review relevant to inspection and machine learning. Section 3 will describe the experimental setup and hardware used. Section 4 will briefly describe the machine learning algorithm and defect detection process. Section 5 will detail the UI and database features and functionalities. Section 6 will present the most recent results of the system. And finally Section 7 will offer a conclusion and our plans for future work.

1.3 Literature Review

Machine learning in visual inspection tasks has made a steady gain in the literature since the popularization of the convolutional neural network (CNN) in [3] for image classification tasks. Further developments outlined in [4] pushed some image recognition tasks above human performance. Meng et al. [5] utilize CNNs to classify defects in composite materials from ultrasonic scanning methods. Kuhl et al. [6] use machine learning techniques to incorporate multiple sensor inputs for the identification of defects on composite aerospace structure.

Benítez et al. [7] outlines the creation of a thermographic inspection system to identify defects in composites structures, with defect identification being accomplished through the use of both the support vector machine (SVM) described in [8] and radial basis function networks. Brüning et al. [9] couples an infrared inspection system mounted on the AFP machine head with several process parameters used in manufacturing to utilize machine learning for the optimization of the process parameters for AFP. The use of SVM for the classification of porosity, inclusion, and delamination in composite structures through ultrasonics is demonstrated in [10]. The use of ML techniques in the evaluation of eddy current data for the classification of defects in composite structures was studied in [11]. The authors utilized a number of algorithms including a U-BRAIN approach that showed promise.

The first iteration of our approach was demonstrated in [12]. In the ensuing period, automated AFP defect detection has remained an area of active research and development. Thus, the continued improvement of our system, with particular emphasis on the development of a user interface (UI) relevant to the USC ML algorithms described in [12], represents scientific worth. The inclusion of an easily interpretable UI elevates our system to a full inspection tool that allows for operator integration, classification correction, and data management and storage through an off-site server..

2. EXPERIMENTAL PROCESS

2.1 Data Acquisition

The collection of data for analysis is done through the Automated Composite Structure Inspection System (ACSIS) developed by Ingersoll Machine Tools. The data acquisition is accomplished using 4 Keyence LJ-V7080 profilometers mounted to a Kuka KR120 robotic arm Figure 1. The profilometers are used to capture a 2D height profile of a surface. This height data is then batched and stitched together to create a 3D mapping of a surface.

Figure 1: ACSIS in operation

The ACSIS software then translates this height data into a grayscale image that has smoothing and contrasting operations performed to provide a clear and interpretable scan of a part as is shown in Figure 2, which shows a part of a scanned course. We can see the differences in the grayscale indicating the differences in the height profiles. The darker patches indicate a lower a dip in the surface while a lighter patch indicates an elevated surface. Through differentiating between these patterns, we distinguish the different defects types, and in turn train the FCN. It should be noted that this is a pre-cure system. ACSIS is intended for use principally with thermoset carbon tows, though there are some preliminary results indicating its ability to capture some dry fiber materials.

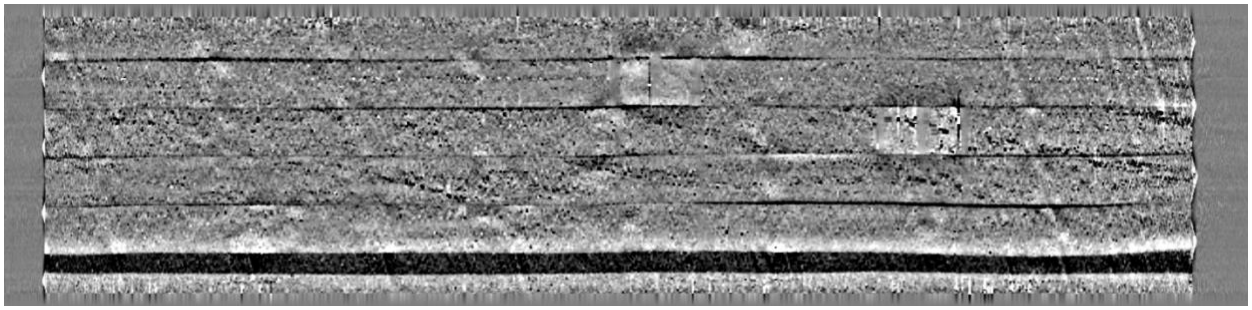

Figure 2: A grayscale image of AFP part from profilometer scan

After inspection, our defect data is logged on a server constructed from a Raspberry Pi 3b+ hosting a MySQL database. The database that was setup for the USC system is conceived in a manner that facilitates communication between three in-house projects. The latter necessitate access to the AFP defects database and to export the information in FE format for further analysis. The server is linked into the lab network, and thus is platform independent and discoverable from any machine on said network. This allows for any potential application that wishes to perform analysis from the defect data to be both theoretically possible and easily constructed on top of the infrastructure provided. This database is not an altered version of the IMT database, but rather a standalone one.

2.2 Image Analysis

2.2.1 Machine Learning Approach

The ML approach described in this paper is based on the network architecture outlined in [13]. The traditional method of object detection, the classification of patches of an image, simply does not have high enough fidelity for the post-inspection applications outline previously. Thus, rather than patch classification, our approach attempts to assign each individual pixel a defect classification. This is accomplished by replacing the standard CNN architecture with all convolutional layer, creating what is known as a Fully Convolutional Network (FCN). Thus, the ability to have an accurate and detailed representation of a given defect is limited only by the resolution of the scanning or imaging system utilized in the data acquisition system.

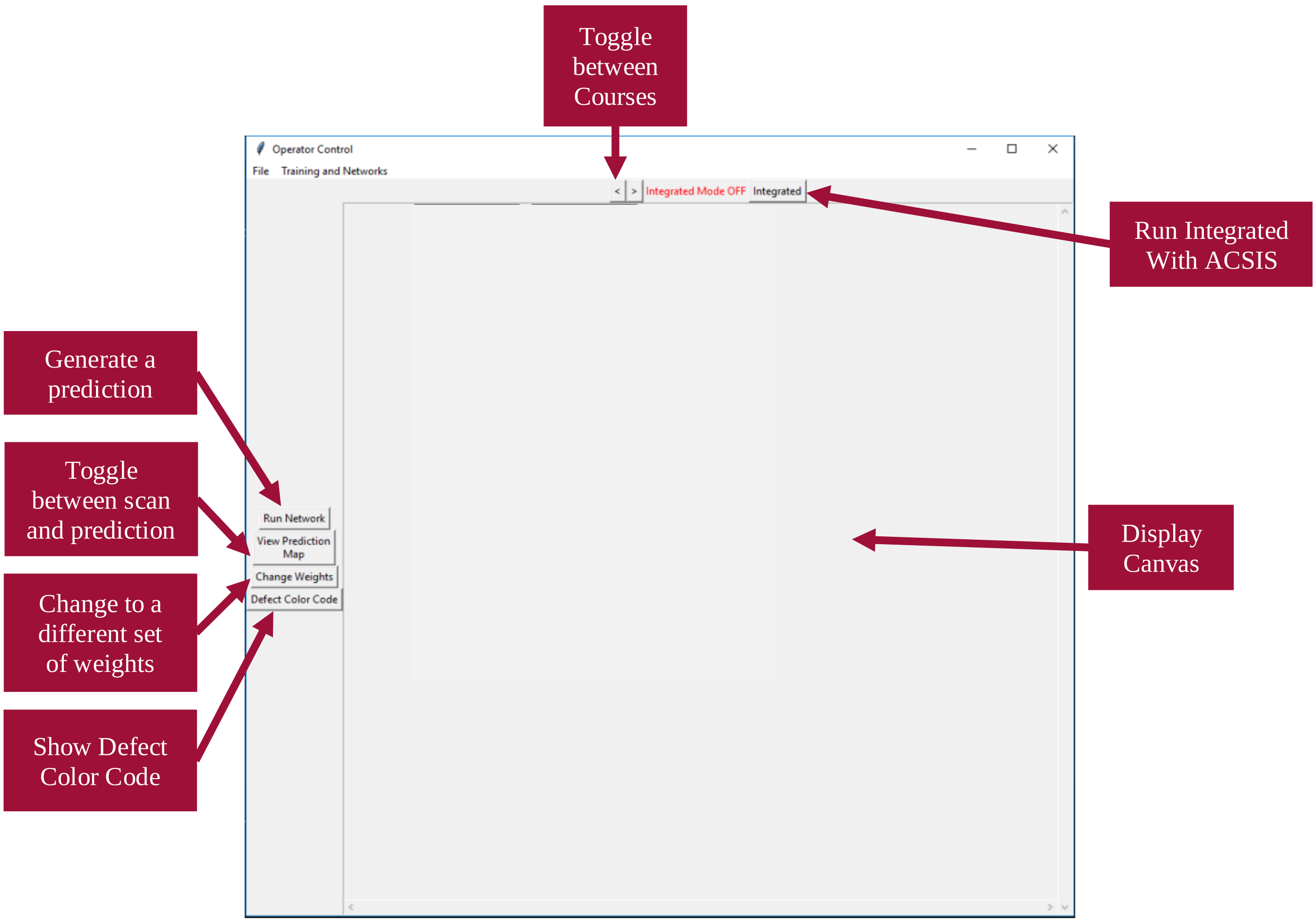

Figure 3: UI Startup window showing the functionalities

Looking to further improve the potential classification accuracy of the system, a FCN variant of the ResNet neural network architecture [4] was constructed. ResNet is notable for having scored a 3.6% top five error rate for the ILSVRC image recognition competition. The network has a total of 15 of the ResNet "skip functions", with 3 convolutional layers allocated to each skip function, bringing the total network size to 45 convolutional layers. Each skip function takes the output of a layer and adds it to the input of a layer further on in the network. This allows for a network to be built that consists of many layers, but this have a comparatively low parameter count. Glorot initialization [14] and convolutional batch normalization were used due to their effectiveness in improving the performance of convolutional networks.

The training was accomplished using an Nvidia Titan Xp GPU due to the ability of a capable GPU to rapidly accelerate the training of deep network models such as ours [15], [16]. Approximately 500 800x800 pixel scan images were used for the training dataset, with testing and validation of datasets of 10 each. In addition, the use of a live system has been tentatively examined and preliminary results of such tests are positive.

2.2.2 User Interface

One of the notable trends in the literature, and what the authors consider a potential reason for the general resistance to the implementation of machine learning capabilities in physical systems, is a lack of comfort in the interaction with said ML systems. Thus, we have aimed to both improve operator relations to our software and alleviate some of the common industry concerns over ML applications. The ML inspection system outlined in this paper can be quickly understood and potentially corrected from an operator user interface (UI). Thus, an operator can react and correct system errors which can be recirculated for retraining of the network. This means that the ML algorithms implemented can be gradually and continuously improved through use. This directly addresses many of the common grievances against ML. Figures 3 to 5 display the mentioned functionalities on the UI.

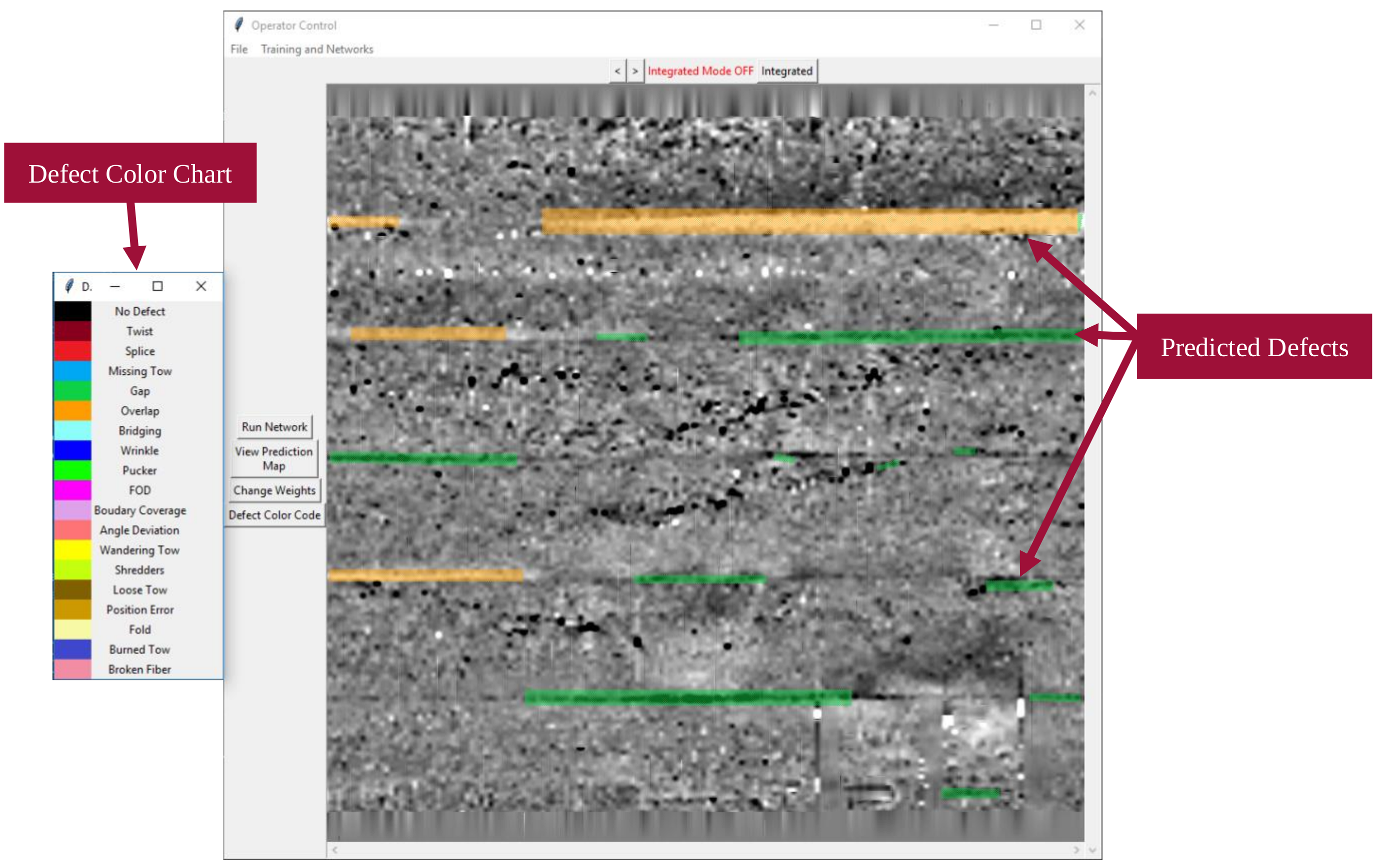

Figure 4: Prediction map and defect type color pallet

The main features of the USC developped UI include the following features, which the original UI provided by IMT included some variation of those features:

1. Display of defects with representative scan image
2. Operator management features and defect trackers
3. Operator correction capacity for misclassified defects
4. Capabilities for operator defined defects
5. Data management feature including export to AFP Defect Database and finite element export
6. Integration with the current IMT ACSIS automated inspection hardware

2.2.3 Data Transfer and Storage

The potential to incorporate defect information into a number of other fields of analysis and to drive further improvement in the AFP manufacturing setting led to the integration of an AFP Defect Database that all defect information could be uploaded to. This database was hosted on a server linked in to the local network and separate python scripts were created to push and pull data from the server. Those scripts were packaged, allowing any additional analysis tool to be developed on top of the server system. A Raspberry Pi 3 B+ was used as the hardware basis for the server and local database operations were accomplished with a MySQL Database instance on the server. The server tracks each part, the corresponding plies on the part, and each defect identified on the ply. In addition, there is a separate section of the database responsible for tracking additional parameters for later correlation with defect production.

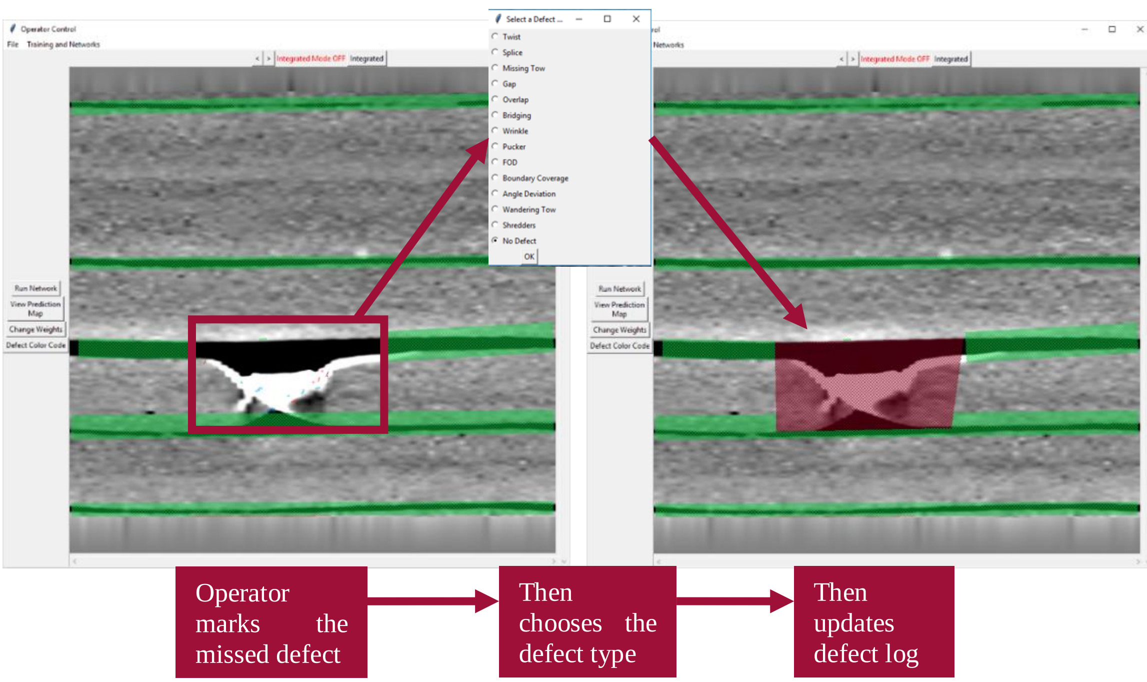

Figure 5: Operator defined defects

The addition of the AFP Defect Database expands the capability of the inspection system by allowing for a number of potential analysis applications to run on independent machines in the manufacturing environment. These additional applications could provide information that can be incorporated into the UI and displayed for the operator. Thus, two way communication of defect data and characterization of data through other tools links the inspection system to the rest of the manufacturing environment in a manner that enables far more integration than a standalone inspection platform. Therefore, the AFP Defect Database can become a linchpin of a smart manufacturing concept.

3. RESULTS

Figure 6 displays a number of testing images and their respective predictions. It can be observed that the software is capable of identifying the locations and types of defects with a fair accuracy. The green color on the prediction maps signify the existence of gaps while orange signifies the existence of overlaps. The UI with functioning inspection capabilities was assessed by an inspection system operator and feedback was given to improve the system. We can make a few notes as to the effectiveness of the defect detection algorithms. Firstly, it should be noted that any change of material has to potential to affect the end accuracy of our system.

This means that while there is a potential to do proper identification of dry fiber or thermoplastic material, it will often skew results in the detection of smaller defects in the case of thermoplastics and the identification of wrinkles and puckers in rough dry fiber.

It can also be noted that while there are a number of defects that our system can detect with a fair degree of accuracy, there a number of classes that are observed a handful of times and thus have limited opportunities to train with. In these cases, our detection algorithms are capable of indicating that a defect is present, but misclassification is a distinct possibility.

4. CONCLUSION

An ML algorithm based on Fully Convolutional Neural Networks (FCN) that allows for pixel-by-pixel classification is used. This permits the software to identify the exact size and shape of a defect in addition to its location on the part. The utilization of a UI gives the system operator precise control over the inspection process and allows for the possibility to correct inaccurate predictions from the ML algorithms. The ability to continually train the FCN from these corrections implies continually improving accuracy in the inspection process. A Raspberry Pi 3 B+ is used to host a USC AFP Defect Database as a MySQL server that can be easily accessed from other software tools. The system's information availability is ideal for integration with rapid analysis tools or machine parameter correlation, moving the system to an Industry 4.0 concept. In addition, the storage of data means that a better digital twin can be instanced, aiding in product lifecycle management (PLM). The ML network was constructed with the use of Glorot initialization for 2D convolutions and batch normalization. The network architecture is a FCN variant of the ResNet network incorporating skip functions every three layers. In total the network is 45 layers deep. An Nvidia Titan Xp graphics card was used to accelerate training and improve prediction speed.

The execution of an AFP inspection system requires more than simply proper identification of defects. Rather, the system outline separates itself through both identification and presentation. Defect information can be utilized in a constructive manner, and the hesitancy of using automated inspection, particularly those consisting of machine learning algorithms, can be mitigated. Machine learning can be applied in the context of a tool rather than a proof of concept. Integrating an inspection system with other manufacturing analysis tools can spur greater efficiency, innovation, and quality.

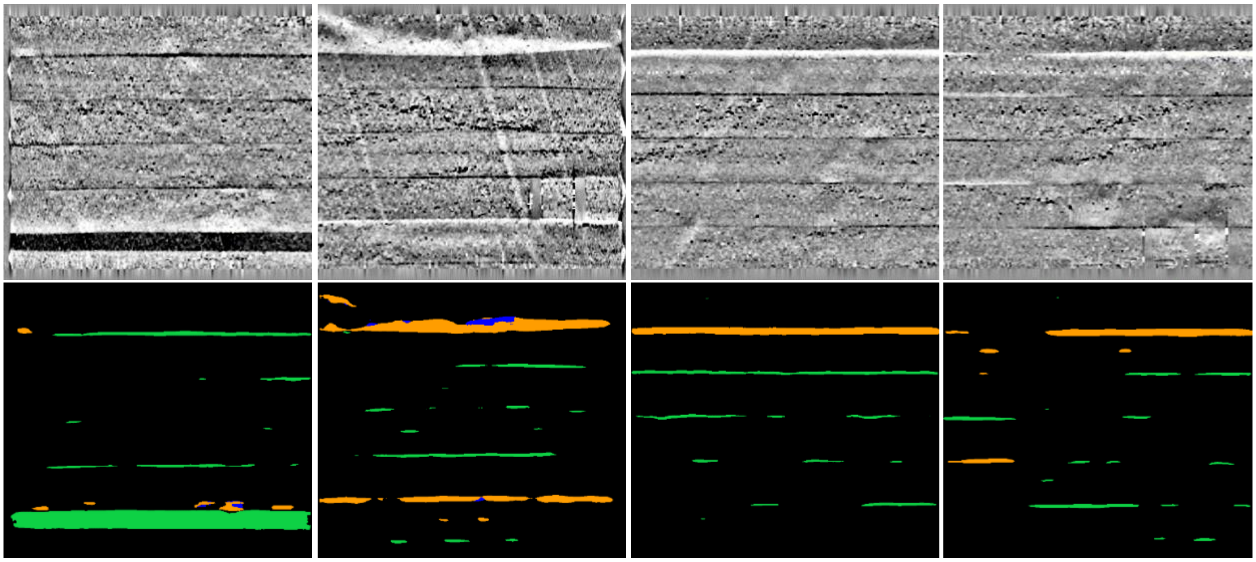
Figure 6: Defect prediction maps showing profilometry scans and their respective defects

There are a number of important notes when creating ML-based systems. It is an absolute prerequisite to have a suitable amount of data for input vectors that have a large number of features. The data must also have adequate distribution over all of the classes that are to be identified. For AFP defects, this implies that the preponderance of gaps and overlaps can pose a potential problem for data collection efforts. This can be mitigated through the application of data augmentation algorithms. In the system presented in this publication, a sine wave distortion was introduced to certain collections of data that were evaluated to be underrepresented in the dataset.

The identification of multiple defects beyond the gap and overlap focus of many of the automated inspection systems is a principle priority of the ongoing development of this AFP inspection platform. In certain cases of rare defect types, our algorithms are often able to identify that a defect is present, but will tend to misclassify the defect type. This is manageable through the UI, however it points to the need for a potential standard AFP defect training set in a manner similar to the ILSVRC or other image recognition and classification competitions. This will alleviate the potential miss-identifications due to the early learning stages, when the system is in 'setup' and/or initial trials are being conducted, i.e. different material setup or such. Concerted work to yield above 1000 training images may be the necessary tipping point to push the current system into being accurate enough for industrial integration with minimal operator intervention. Developing this additional training data will be a focus for the continuing improvement of inspection system. A number of additional tasks for future work include:

- Expanding data management tools
- Exploration and optimization of profilometery settings
- Developing network retraining capabilities from operator input

An exercise in operating the software in a live production environment for an extended period of time may yield useful information about the performance and improvement of the system with time. Thus, while these results are still squarely under the regime of preliminary, it is expected that a full understanding of the system capabilities will follow in the near future.

Additional area of potential work includes the integration of our system with steered tow designs. Preliminary investigation indicates that fiber steering produces a number of defects including wrinkles [17]. Inspection can also be utilized as an experimental check on any number of path planning operations that may contribute to the defect production process [18].

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