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# Using Artificial Intelligence to Recognize Wheat Stripe Rust Disease

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## ABSTRACT

Artificial intelligence has great potential in agriculture. It can be used to fight food insecurity, climate change, and plant diseases. This is becoming increasingly important due to the increasing world population. AI allows the workload to be placed on technology instead of people. Though it is designed by humans, AI can become better, more advanced, and more efficient. Already, AI is more precise, available, and faster at recognizing plant diseases than trained professionals. This allows the disease to be eradicated by solutions that the same AI can generate before the disease spreads and destroys entire fields. Artificial intelligence algorithms can be created through machine learning, and humans can train the algorithms to automatically recognize the plant disease known as wheat stripe rust. These recognitions can be used to take the proper steps in preparation to keep wheat crops protected. Furthermore, the wheat artificial intelligence model can be integrated into apps, such as Nuru, which are already helping farmers identify and combat disease. Through further research, the potential of artificial agriculture is boundless because the same process can be applied to recognize other diseases and applied around the world.

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## ACKNOWLEDGEMENTS

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## Chapter 1

## Artificial Intelligence in Agriculture

The world human population is steadily increasing, and it is estimated to reach about 10 billion by 2050 (Talaviya et al., 2020). This has many different connotations, but one of the main ones would be a demand on energy. Many of the current sources of energy, such as fossil fuels, generate massive amounts of carbon dioxide, adding to the ever-present issue of global warming. Another consequence of an increasing population would be the heightened emphasis on food security. With so many different people, the demand for food increases and the agriculture industry becomes more important than ever. One of the best ways to increase food production would be to focus on crops and protect them from disease or pests. Fortunately, along with the increasing human population, there also comes an increase in knowledge and technological advancements, such as artificial intelligence, that hold the solutions to these major world issues.

Artificial intelligence can be defined as a computer's ability to execute work that would normally require human intelligence (Copeland, 2020). This can include anything from simply being able to recognize something to being able to reason and problem-solve. Most people interact with and use artificial intelligence everyday. For example, Siri, Alexa, email spam filters, Netflix suggestions are all examples of artificial intelligence. They are mainly either reactive machines or limited memory AI (Reynoso, 2019).

Reactive machines and limited memory differ in the amounts of information they hold (Reynoso, 2019). Reactive machines are a simple form of AI because it does not store a large amount of memory. Without relying on past experience, it will react to the same stimuli, in the exact same way, each time, making it reliable and useful for monotonous tasks that humans get tired of quite easily. Spam filters are a good example of this. A more advanced and common type of AI would be limited memory AI. As the name implies, this type of AI can hold more information than reactive machines and rely on this information to complete more complex tasks (Reynoso, 2019). Machine learning or deep learning are ways that humans train AI models by feeding them with data, allowing the AI to recognize patterns. Self-driving cars use memories of past events, incoming sensory data, and pattern recognition to make quick and safe decisions, so it is a limited memory AI (Reynoso, 2019).

Though limited memory AI has its restrictions, it can still hold vast amounts of knowledge and data which can be adapted in certain situations. For example, communication can be a limitation among humans because of a limit in language comprehension. AI, on the other hand, can hold multiple languages and use the proper language when interacting with certain people through voice and language recognition. Also, being able to hold all this information, AI can match or even surpass trained professionals in medical diagnoses. University Hospitals Birmingham compared the accuracy reports of AI to the doctors, and the results indicate that AI correctly diagnosed diseases 87% of the time, whereas doctors diagnosed correctly 86% of the time (Liu et al., 2019). This is an amazing capability and though it is not well-tested enough to incorporate this AI into all human diagnoses, this technique alongside the multiple language features of AI can be applied to lower risk situations to recognize plant diseases.

AI is useful for diagnosing plant disease because with the increasing population, more crop fields will emerge due to higher food demands. The maintenance of the crop fields is imperative, but this means requiring knowledge and solutions at your disposal. Usually, an expert with the capabilities of diagnosing plant disease would be called in but there are only so many trained professionals available. It takes time for them to travel, come up with a diagnosis, collaborate with others to double check, and get a translator to communicate their diagnoses to farmers that do not speak the same language. These limitations do not apply to AI. AI is accurate, available, fast, reliable, and adaptive to the needs of the people. The usage of artificial intelligence in agriculture is becoming more common, and it has been integrated in the agricultural field to fight food insecurity, combat effects of climate change, and aid farmers recognize and eliminate plant diseases.

## Food Insecurity

Food insecurity can be caused by a multitude of different factors such as low crop yields, low fertility, loss of soil health, limited water, too much pesticides, and more (Talaviya et al., 2020). Different artificial intelligence models have been used to solve many of these problems. Already, researchers at the UK's University of Birmingham, are integrating artificial intelligence into nanotechnology to help farmers increase the health of their soil to keep their land fertile and their crop yields high (Zhang et al., 2021). One example of how this is being done is by using artificial intelligence to control the administration of pesticides through nano-agrichemicals (Huang et al., 2018). The optimal control of pesticide administration is a form of precision agriculture.

Precision agriculture refers to collecting and analyzing data with the goal of being able to make decisions that would improve quality and efficiency in agricultural practices (Zhang et al., 2021). Pairing precision agriculture with artificial intelligence would allow farmers to have access to data in real time and adjust their management techniques accordingly. For example, farmers would be able to determine the optimal amount of fertilizer their soil needs to maximize benefits through soil analysis. Whereas farmers would only be able to focus on one factor at a time, AI would has the neural network and sensors to input all the factors, such as temperature, pH, water absorption, factors that farmers might not even consider, such as vitamin concentrations, into its algorithm to give a much more accurate and faster suggestion for fertilizer needs at once. The soil analysis can further be used to check for pests, overall health of the soil, avoid nutritional deficiencies, and more (Sennaar, 2018). It is a way to bring awareness of issues to the farmers before they begin impacting crop yields and lead to decreases in food security.

Other approaches of integrating artificial intelligence into agricultural practices include crop monitoring and irrigation. To minimize water waste, thermal imaging cameras that are enabled through artificial intelligence can be used to increase efficiency. The AI makes predictions relating to evaporation, evapotranspiration, and weather (Mor, 2021). This means the AI can consider all the sources of water available to the plants, and irrigation can be made available to the plants only when necessary, reducing water waste. Another advantage to this AI would be that it can be controlled automatically without human intervention. Furthermore, changes in weather patterns and how they may impact crops are important factors to monitor. Although humans have been monitoring weather patterns for decades, AI has become advanced enough that with enough data, they can more accurately indicate signs of flood or drought with enough advance warning to allow the farmers to take the appropriate measures to protect their crops and continue monitoring their health (Mor, 2021).

**Climate Change**

Climate change is another issue in agriculture that could be partially dealt with through the use of artificial intelligence. The increasing concentration of carbon dioxide in the atmosphere has a huge impact on plants due to the increased heat, which impacts soil, water needs, the nutrient cycles, and the overall health of the plants (Zhang et al., 2021). Artificial intelligence would be the perfect way to combat this. Predictive agriculture analytics would be able to collect data of the changing factors, such as higher temperature, fluctuating weather patterns, and increased evaporation rates due to climate change, make predictions on the different impacts, and then adjust accordingly for the best health of the crops (Zhang et al., 2021). Although humans can measure these changes too, allowing AI to take over this responsibility allows for a quicker and precise estimate of the impacts, so that the proper adjustments, such as increased shading or reduced soil acidity can be implemented sooner, rather than later. Climate change is unfortunately not going away anytime soon, so new technological advancements must be applied to minimize its effects.

The effects of climate change can also be measured and predicted by AI on a larger scale as well. The predictive analytics available to AI are not limited to agriculture, but they can measure large scale impacts that have indirect effects on the agricultural field. For example, AI models that interpret climate data, weather forecasts, and locate sources of carbon emissions across different geographical locations can provide valuable information to policymakers (Zennaro et al., 2021). The more data the policy makers have access to, the better they can create changes that prevent rising sea levels, lessen the impact of hurricanes, protect natural habitats, discourage deforestation, all events that have an indirect impact on agriculture.

These predictions can also be useful to figure out the solutions to mitigate climate change. For example, there have been models such as the eXplainable Artificial Intelligence (XAI) model that are used to anticipate the daily energy consumption of a building within different scenarios (Chakraborty et al., 2021). These predictions can be used to figure out the most efficient way to make use of green energy so that we aren't so reliant on fossil fuels. Being able to predict how alternative energy sources would manage the energy consumptions of buildings would allow us to reduce waste of time and money by eliminating scenarios that would not meet the anticipated daily needs (Chakraborty et al., 2021).

## Plant Diseases & Pests

A major factor that farmers are trying to minimize in agriculture through the use of artificial intelligence would be disease. Computer vision is a type of AI that is being used in Leones, Argentina (Allen, 2019). A drone with a computer vision enabled camera is able to glide across 150 acres of farmland and scan for disease and pests in wheat crops. Farmers use these drones to keep an eye out for early signs of disease, so they can prevent it from spreading and reduce the loss of healthy crops. These drones are useful because trained pathologists are not always available and may be limited to how many fields they can visit. The drones, however, can be deployed by farmers working with the Taranis company routinely, are much faster, and can cover more areas and fields (Allen, 2019). In some cases, the AI used by the machine learning models may even be more accurate than the experts.

A machine learning AI model used to detect plant disease based off of foliar symptoms was created by Penn State's PlantVillage. It was incorporated into a free app, called Nuru.

Farmers can use the camera on their phones through the Nuru app and bring an image of a leaf with possible disease symptoms into focus. The deep learning object detection model built into the Nuru app runs a real-time analysis on the leaf image and then gives information about the health of the leaf to the farmer. For example, the app can inform the user that there are symptoms of fall armyworm, a common pest in Africa that tends to eat maize plants. Furthermore, the app can also provide advice on how to deal with the pest, prevent it from spreading, and the next steps to take.

In addition to detecting pests, the Nuru app is very efficient at detecting disease. Cassava is a massive source of food in Africa, South America, and Asia (Pariona, 2019), so cassava disease can have major impacts on food scarcity. It is especially prominent in East Africa, so the Nuru app has been popular in this region. A study published in Frontiers of Plant Science compared the detection accuracy of the Nuru app to the accuracy of agricultural extension agents and farmers (Mrisho et al., 2020). It was found that farmers had the lowest accuracy reports with an accuracy report of 18-31% (Mrisho et al., 2020). Although agricultural extension agents had a higher accuracy than farmers (40-58%), the Nuru app was the most accurate with an accuracy of 65% (Mrisho et al., 2020). The study also demonstrated that the Nuru app was effective in teaching farmers about the disease and increasing their detection accuracies.

# Chapter 2

## Wheat Stripe Rust Disease

Researchers in PlantVillage are using a similar strategy that was used to create the Nuru app to help farmers identify and find solutions to this wheat stripe rust disease. Wheat rust is a disease that is particularly giving trouble to farmers in Africa & Asia. The three main types of wheat rust would be stem, stripe, and leaf rust (Jaleta et al., 2019). A case study in 2011 found that stripe wheat rust spread over 33% of Ethiopia's wheat area (Jaleta et al., 2019). This is worrisome because wheat crops are a major contributor to food and business for many African farmers. It is imperative to educate farmers about this disease and the strategies they can implement to decrease its effects.

*Puccinia striiformis*, more commonly known as stripe rust or yellow rust disease on wheat, can commonly decrease crop yield by 40%, but it has also been known to eliminate entire fields of wheat (Agriculture Research Service, 2016). The rust is caused by a fungus called *Puccinia striiformis* Westend f. sp. Tritici, an obligate parasite (Martinez et al., 2015). It produces urediniospores that can be 20 to 30 um in diameter (Martinez et al., 2015). These urediniospores, spread by wind, are what gives the symptoms, the bright yellowish orange rust-like appearance (Figure 1) (Agriculture Research Service, 2016). The disease is most common in higher elevations and at cooler temperatures. Infection is most prominent at temperatures between 10-16°C (Martinez et al., 2015).

**Figure 1: Wheat Stripe Rust Symptoms**

To control the infection, farmers can monitor their fields for symptoms of rust, such as a yellow powder on the leaves. Chemical controls through fungicide sprays can prevent the disease from spreading (Agriculture Research Service, 2016). Since there are some varieties of wheat plants that are resistant to stripe rust due to resistant genes called Yr, genetic control can also be utilized (Agriculture Research Service, 2016). Seedling resistance is controlled by a single gene and will last through the entire wheat life cycle (Martinez et al., 2015). Adult plant resistance develops as the plant ages (Martinez et al., 2015). Researchers in PlantVillage are actually trying to integrate artificial intelligence into a training model to help farmers identify this pest and give them the tools to combat wheat rust.

# Chapter 3

## Work in PlantVillage

Since the Nuru app has been shown to improve real time diagnosis capabilities of diseases such as cassava and fall army worm, a similar model can be created to detect wheat stripe rust by using the same process. This work is imperative because although the symptoms of wheat rust can be apparent, it is not as easy to distinguish between the different types of rust. It can be difficult for farmers to distinguish between actual wheat stripe rust compared to leaf or stem rest. An AI model can be trained to accurately distinguish between the three different rust types through subtle details that most people would not be able to pick up on. This process consists of collecting and organizing the data as images of the different rust types. Then the data is labeled and the wheat stripe rust is specifically highlighted. This annotated data can be used to create the machine learning models. Advanced image segmentation, tiling techniques, and field tests are then used to refine the detection accuracies. Finally, this AI model can be incorporated into an app, like Nuru, so that farmers can have free access to them.

### Data Collection

The strategy starts with data collection in the form of taking high quality images. In October of 2018, pictures of leaves with wheat stripe rust were taken in the Bale Zone of Ethiopia by Yoseph Alemayehu and Peter McCloskey in fields that were confirmed to be infected with wheat stripe rust by trained experts. Each image has only one leaf infected with rust and is usually held vertically so that the entire leaf can be seen (Figure 2). Some images may have body parts because the photographers hold the leaf flat so that the leaf can be in the center focus, and the rust disease can be clearly seen.

**Figure 2: Examples of Collected Images of Leaves Contaminated with Wheat Stripe Rust Disease**

The more images there are, the more the AI model has to work with, allowing it to be more exact and refined. These pictures are the starting point in teaching an artificial model to learn how to recognize the disease automatically, so they must be of high quality. Also, it is important to have a diverse variety of images as well so that the AI model will be able to recognize the wheat rust on different shades of leaves, at different angles, in different amounts of light, etc.

**Data Sorting**

The data is then organized by crop, disease, location, or variety, and the low quality data is excluded. Low quality data can take many forms. It could be due to low light, making it difficult to see the rust. Blurry pictures would be problematic because there would not be an accurate way of knowing where the rust begins and the leaf ends. Images with the leaves being too far would make it difficult to see the rust. On the other hand, images that are too close would take the rust on the leaf out of focus. Images that have these issues are of low quality (Figure 3), so they must be excluded to avoid decreasing the accuracy of the machine learning model. Next, the annotations can begin to create the initial data set.

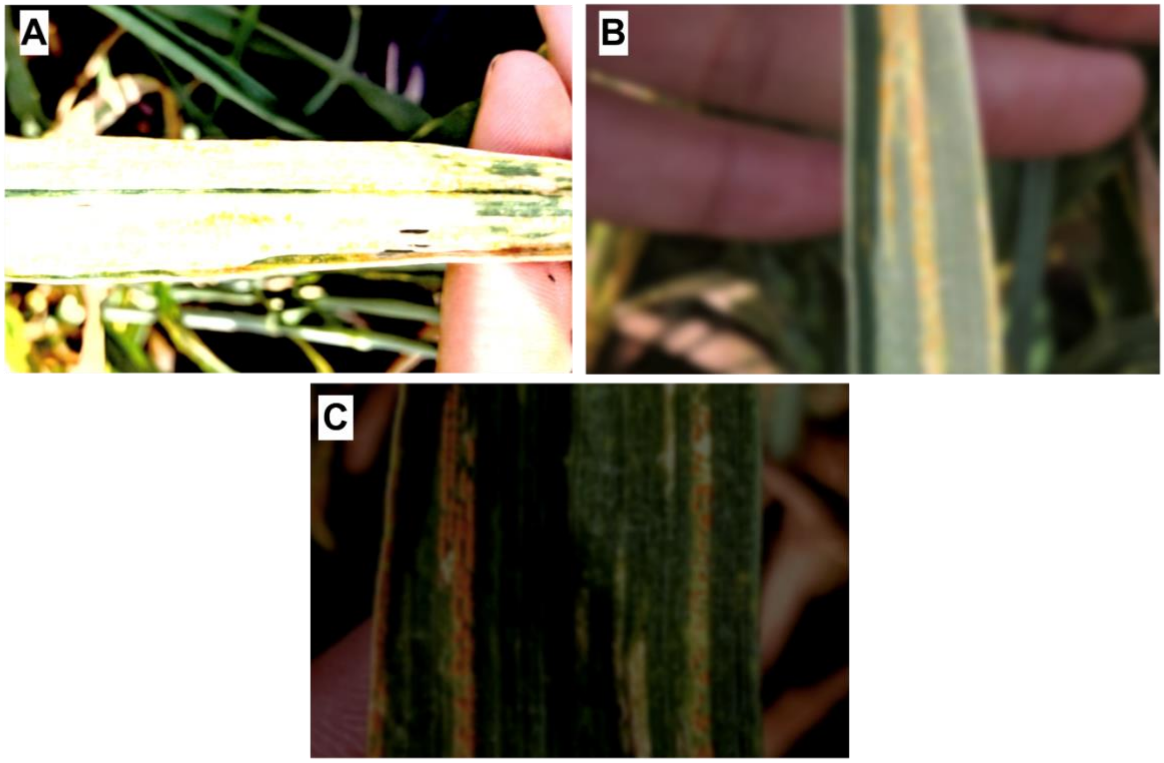


Figure 3: Examples of Excluded Images due to: (a) light saturation, (b) blurry image, (c) too dark

## Annotations

Trained undergraduate researchers at Penn State University carefully label the provided input images (Figure 4) first few hundred images. In May of 2021, the first images of the wheat stripe rust began to be annotated with labels using the Pixel Annotation Tool, an open source and free data labeling tool used in annotations of previous AI models, such as the cassava model (Mrisho et al., 2020). Originally, the first few annotations were done with a computer and mouse, but to enhance the quality and accuracy, a Creative Pen Tablet and pen from Huion were used instead (Figure 5).

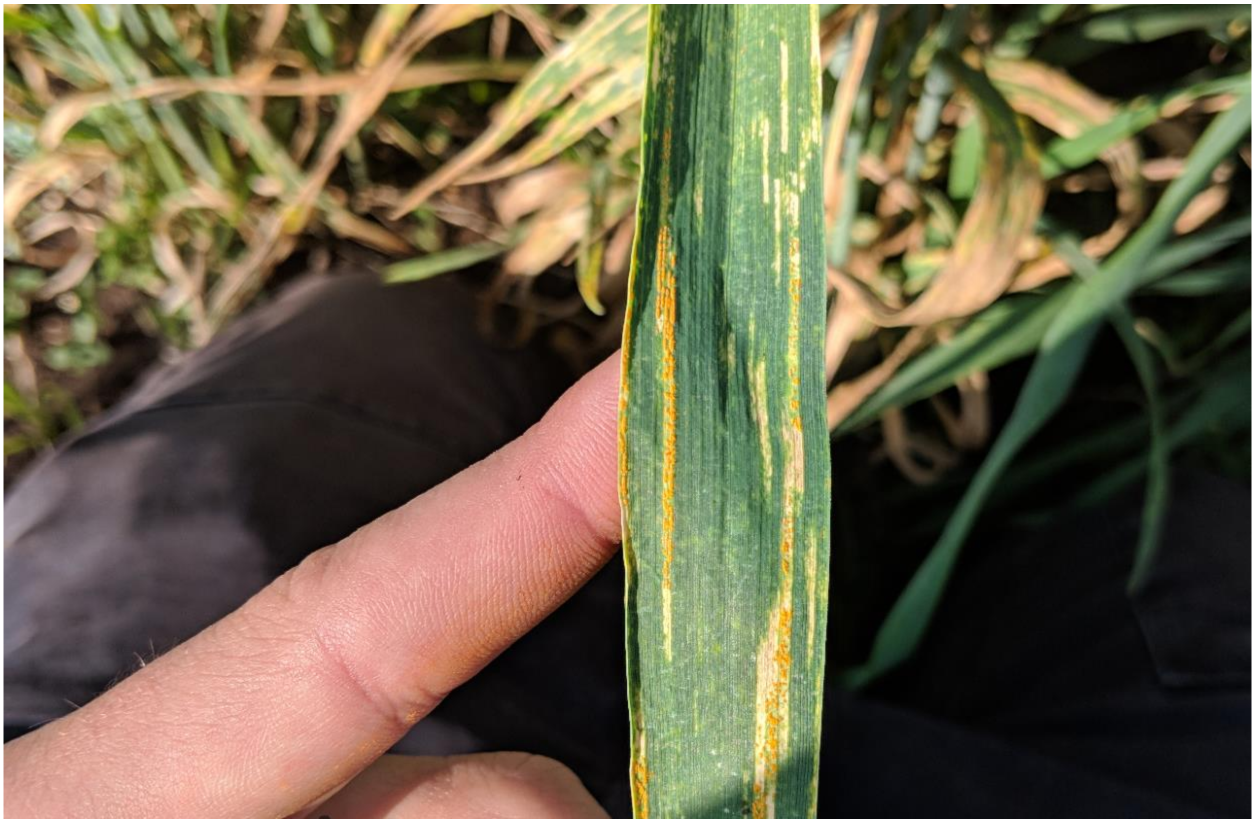

Figure 4: Input Image for Wheat Stripe Rust

Figure 5: Creative Pen and Tablet Utilized to Enhance Annotation Accuracy

The annotations created by the undergraduate researchers were the manual masks (Figure 6), where the pixels of the input image were assigned a class label, or classification. The pixels of the images that were prioritized were the leaf, labeled in green, and the stripe rust, which was labeled in orange. All other parts of the image, such as other leaves, body parts, soil, were labeled as the background, which used a white mask. Then a watershed mask is applied based on the manual mask.

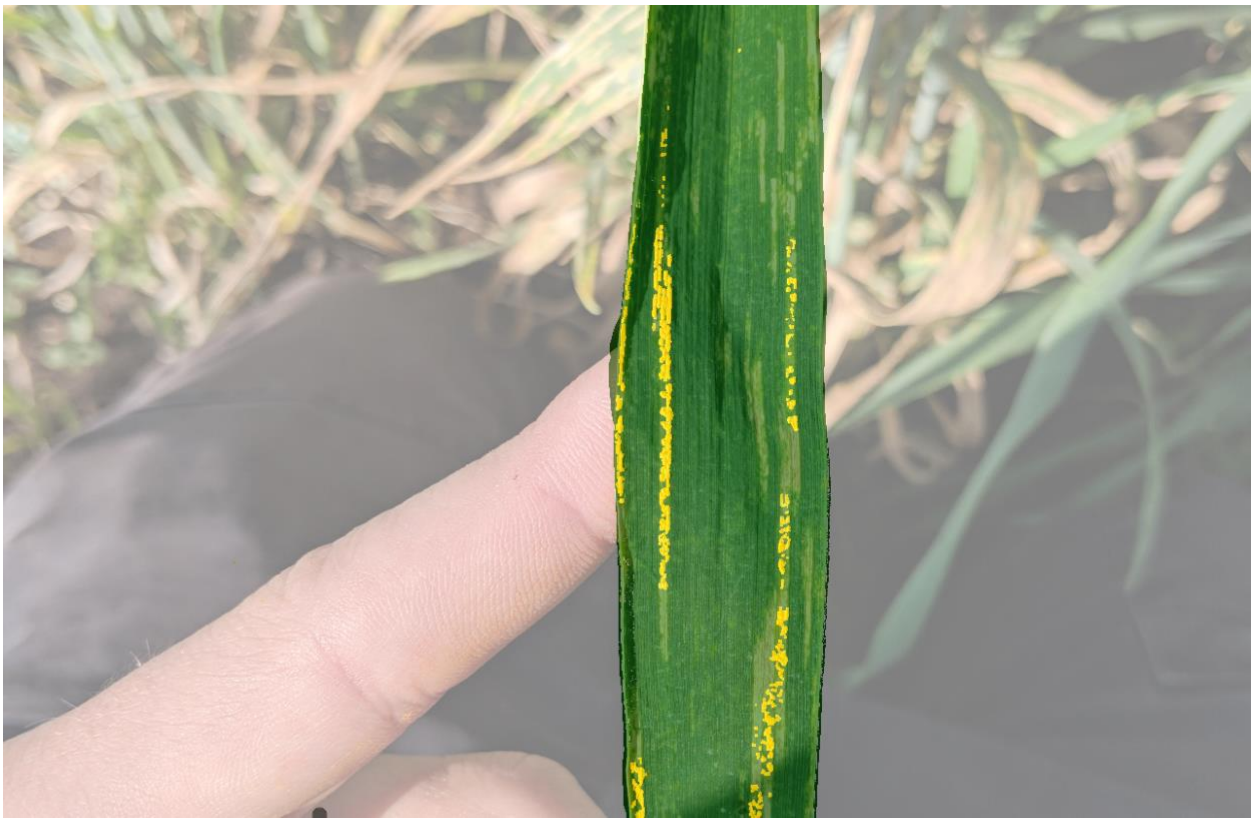

**Figure 6: Manual Image for Wheat Stripe Rust**

Watershedding is a common technique in computer vision that translates the annotations into something the AI model can read and understand (P. C. McCloskey, personal communication, February 28, 2022). It does this by assigning a class label to all the remaining pixels. The class labels of the watershed mask are dependent on the class labels assigned to the neighboring pixels of the manual mask. The algorithm of the Pixel Annotation Tool classifies "similar" neighboring pixels with the same classification (Figure 7). "Similar" can be defined as RGB values that are within a given limit of each other (P. C. McCloskey, personal communication, February 28, 2022). The watershed masks are important because they are used as the ground truth labels. Ground truth labels means that they are the targets of the AI model, in this case the stripe rust on the leaves will be recognized through the watershed masks, not the manual masks.  Once complete, the annotations are double checked by another undergraduate researcher before they can be used to create the AI training model.

**Figure 7: Watershed Image for Wheat Stripe Rust**

**Training Model**

The training model is created by the deeplab team using the exception_65 architecture from Google's TensorFlow, which is a free and open-source software for creating artificial intelligence models with machine learning. To train the AI model to recognize the wheat stripe rust, transfer learning was used. Transfer learning involves fine-tuning the specific weights of PlantVillages' dataset onto a model that was pre-trained on a basic dataset. The first model was trained on May 10th, 2021.

Image segmentation and tiling techniques were required to make the AI model more precise. At first, the AI model was only able to distinguish the leaf from the background, but it could not reliably identify the wheat rust on the leaves. One possible reason for this error could be due to the relatively small size of the rust on the leaves. Tiling was used by splitting the image into 3x3 image segments, so a total of 9 totals were constructed. These were individually used to train the model so the rust took up more space in the tiled image and looked bigger compared to the complete, original image. The AI model goes pixel by pixel, working off what it learned from the annotations created from humans, to focus on the rust and distinguish it from the leaf. The tiling technique allowed the AI model to be precise enough to not only distinguish the rust from the leaves, but it also allowed it to consistently diagnose wheat stripe rust from other types of wheat rust, such as leaf rust or stem rust.

This most recent model, v8, was trained about a month after the first one on July 6, 2021. The stripe rust's specific Intersection over Union (IoU) value, used to assess the accuracy of the AI model, is 0.336. In this case, the IoU value is referring to the amount of overlap between the amount of rust that the AI model predicts and the actual rust present on the leaves. The value is usually between 0 and 1, with 0 meaning there is no accurate prediction and 1 means that the AI model predicted the amount of actual rust perfectly (Hofesmann, 2021). The overall mIoU with all three rust types is a bit higher at 0.438, but the model still has room for improvement. This is evident in the quantity of rust it recognizes. Although it is able to recognize what type of rust is on the leaf now, it is not accurately recognizing how much of the leaf is covered in rust. To improve the accuracy of the diagnosis, splitting the image into more tiles could be a potential solution. Another possible way to increase the accuracy would be to use more images with more precise annotations.

# Chapter 4

# Future Steps

## Field tests

Once the AI model is trained enough to consistently give accurate results, the model is trained in the field. The current model is predicted to begin the field tests in Nepal in March 2022. The field tests would consist of incorporating the model into a basic test app. This app would be used in the field to assess how the detection model runs in the real environmental conditions. The data from these surveys is collected and the training model is refined through until it is more accurate.

## Integration and Access

Eventually, the training model can be integrated into an app, such as Nuru. Farmers can simply use their phone cameras to scan a leaf through the Nuru app, and the artificial intelligence algorithm will be able to identify the impacts of wheat rust disease. One of the more useful features of the Nuru app is the solutions that it offers to the farmers after it detects the presence of fall armyworms or cassava disease. Ideally, the app would do the same for wheat stripe rust and offer advice on how to decrease the spread, such as applying fungicide. The work is not done though, because the app is always monitored and updated for bug fixes, accuracy, and enhanced features.

One feature that is especially helpful to international farmers would be the multiple languages programmed into the app. For example, Swahili is a common language of East and central Africa, so the farmers who do not speak English can switch the app's language to Swahili. Now, the diagnosis they receive will be in a language they are comfortable with and even the advice will be written in Swahili. There are also efforts to integrate a voice command function into the app, so that those who cannot read or write are still able to utilize the app's feature by simply speaking to it. Other languages that Nuru is able to communicate would be English, Twi, Hindi, and French.

With all these capabilities, one would assume that Nuru is expensive and requires a large amount of cellular data or Wifi to function, but this is not true. The app was created with its users in mind. Many of the farmers who are the targets of this app already have to spend most of their money to maintain their crops and keep them free from disease, so Nuru is an inexpensive app. It can be downloaded for free for Androids and iOS devices. Also, the multitude of locations that the app would be utilized are remote and there would be little to none network service available. That is precisely why Nuru is able to be used while farmers are offline, and it does not need an internet connection to diagnose disease and give management techniques.

# Chapter 5

## Further Applications

This same model can be used for other diseases. PlantVillage is taking similar steps to create other machine learning models to detect wheat blast. This wheat blast model is currently in the annotations stage of machine learning (Figure 8). Wheat blast is a disease that afflicts plants in many countries, such as Pakistan, India, Brazil, and much more (Mottaleb et al., 2018). In 2005, wheat blast was particularly persistent in Brazil. Even after multiple applications of fungicides, the disease still managed to reduce the crop yield by 14-32% (Urashima et al., 2009).

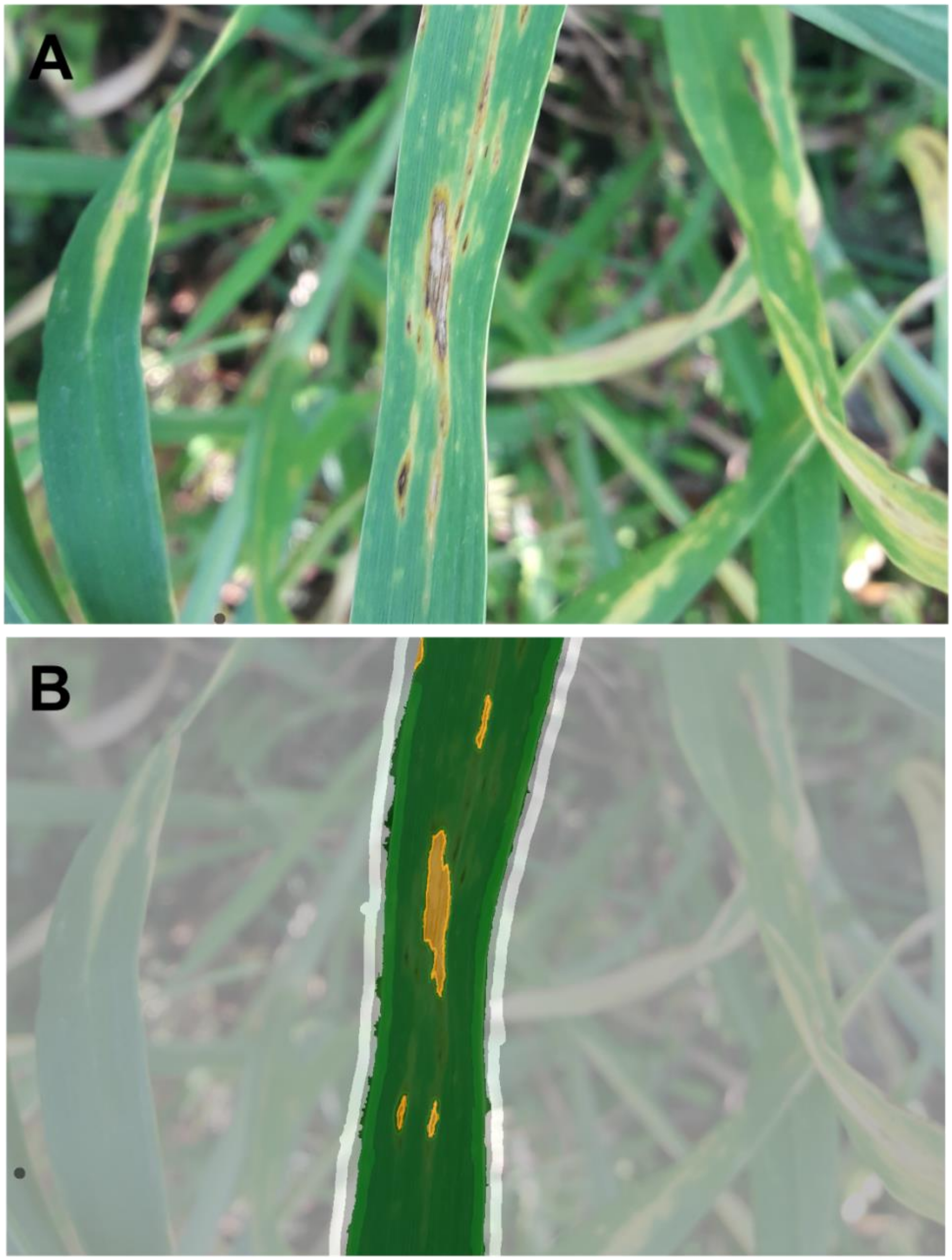


**Figure 8: Example of Wheat Blast: (a) without and (b) with annotations**

An AI recognition model for wheat bipolaris disease is also currently underway at PlantVillage to fight its devastating effects. The same process is being used, but with different types of images. For this disease, images were taken under the microscope to get more details of the disease structure (Figure 9).

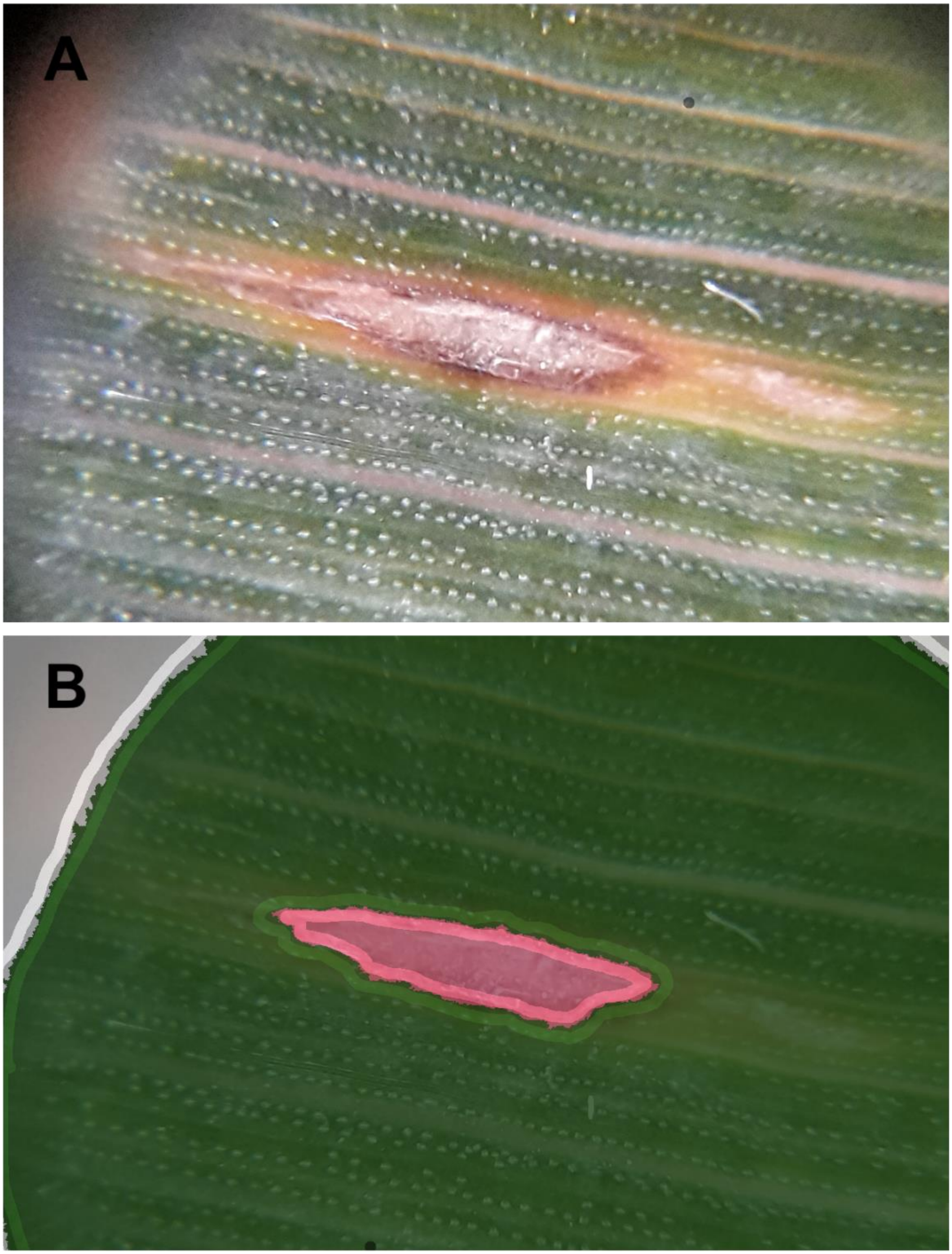


**Figure 9: Example of Microscopic Wheat Bipolaris: (a) without and (b) with annotations**

Another training model PlantVillage is working on is tree detection. Using satellite images of areas of lands, the researchers are able to annotate the trees, the roofs, roads, and backgrounds. These images will eventually be used to create a model that can automatically detect how many trees are in a certain area. The AI model is created through a similar process of machine learning (Figure 10). This information is vital because it will provide insight into how much land is available to plant new trees. Given time, farmers can use the new trees for wood, a source of income, protection, and a way to combat the effects of climate change.

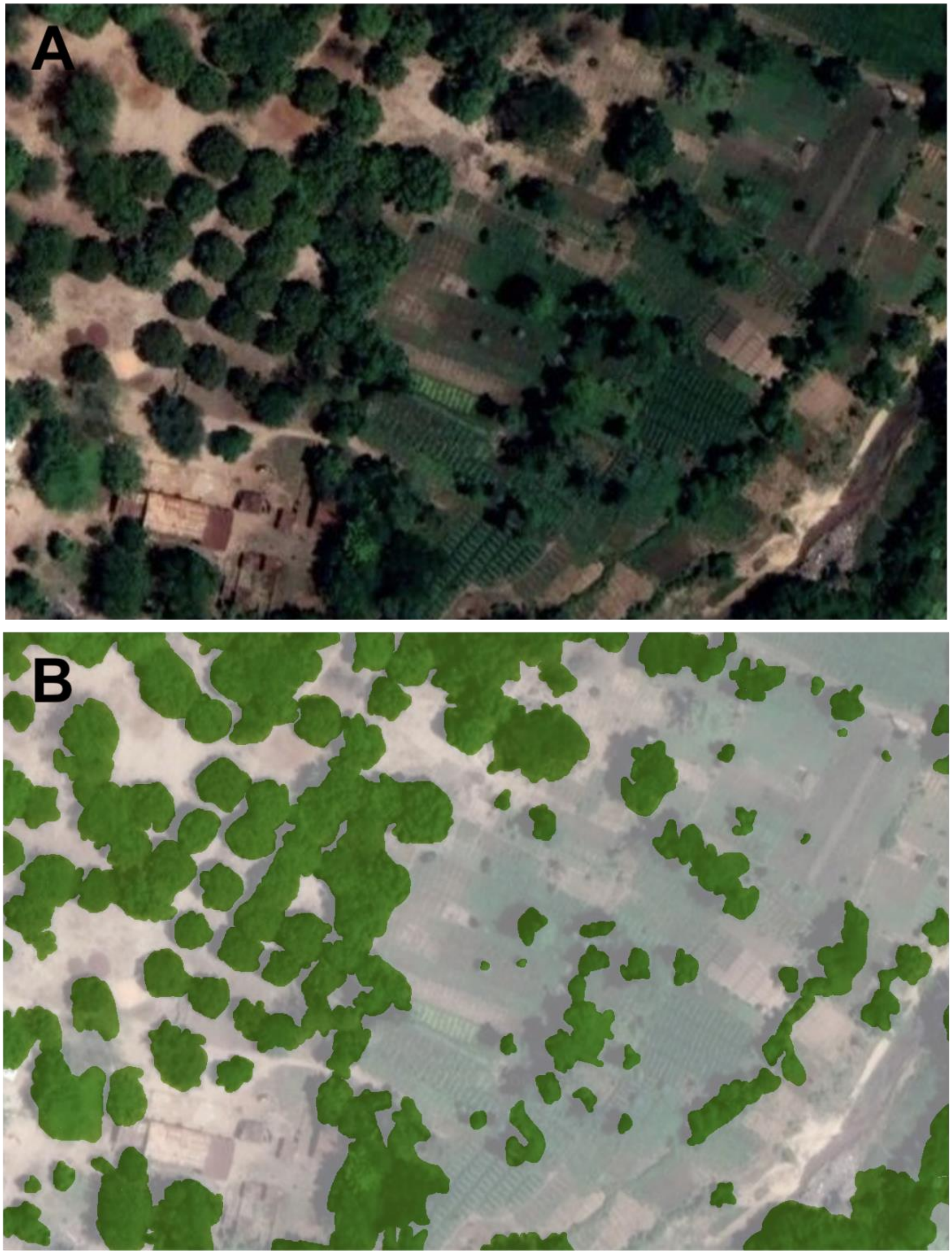


**Figure 10: Example of Tree Detection: (a) without and (b) with annotations**

Artificial intelligence has great potential in agriculture. Precision agriculture has been used to improve the overall health of the soil and quality of crops. In this way, it can be used to fight food insecurity. The predictive nature of AI has been used to prepare farmers for the impacts of climate change and take the proper steps to minimize the damage. Machine learning is already being used to fight diseases and pests. This same method is being used to create AI models that will provide real-time diagnosis of wheat stripe rust disease. With each day, the models are being refined, their accuracies improve, and they are integrated in ways to increase the accessibility to those who need it the most.

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**ACADEMIC VITA**

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## EDUCATION

The Pennsylvania State University, State College, PA June 2022
Bachelor of Science in Biology, Neuroscience

## RESEARCH

Penn State University, State College, PA May 2021 - Present
*Undergraduate Researcher of PlantVillage*

Penn State University, Center Valley, PA November 2019 - April 2020
*Undergraduate Researcher of Health of Laurel Run Stream*

Penn State University, Center Valley, PA September 2018 - October 2018
*Undergraduate Researcher of Using dsRNA to Control Spotted Lanternfly Populations*

## WORK EXPERIENCE

The Pennsylvania State University, State College, PA August 2021 - Present
*Learning Assistant*

Phoebe Richland, Richlandtown, PA May 2020 - Present
*Certified Nursing Assistant*

The Pennsylvania State University, Center Valley, PA August 2019 - Present
*Peer Tutor*

The Pennsylvania State University, Center Valley, PA August 2019 – June 2021
*Note Taker*

The Pennsylvania State University, Center Valley, PA August 2019 - May 2020
*Biology 03 Instructor*

## ACTIVITIES

The Pennsylvania State University, State College, PA August 2021 – Present
*Sher Bhangra, Dancer*

The Pennsylvania State University, State College, PA May 2020 – Present
*Council of Commonwealth Student Governments, Director of Academic Affairs*

St. Luke’s University Health Network, Bethlehem, PA May 2019 – March 2020
*Volunteer*

The Pennsylvania State University, Center Valley, PA August 2018 – May 2020
*Honors Club, President*

The Pennsylvania State University, Center Valley, PA August 2018 - May 2020
*Community Heroes Club (Service Club), President*

The Pennsylvania State University, Center Valley, PA August 2018 - May 2020
*Student Government Association (SGA), Academics Chairman*

**AWARDS**

CCSG Central Staff Membrane of the Year (2021)
Leader of the Year Award (2020)
Outstanding Tutor Award (2020)
Biology Student of the Year (2020)
Lighthouse Trustee Scholarship (2020)
Division of Undergraduate Studies Scholarship for Exploratory Students (2019)
Academic Excellence Scholarship (2019-2022)
Moyer Trustee Scholarship (2018)
Schreyer Scholar (since 2018)