

Eberswalde University for Sustainable Development – HNEE
University of Applied Sciences
Faculty of Forest and Environment

Warsaw University of Life Sciences WULS – SGGW in Warsaw
Faculty of Forestry

Muhammed Sinan
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Semantic Segmentation of dead trees (*Picea abies*) using deep learning

Semantische Segmentierung von abgestorbenen Bäumen (*Picea abies*)
mittels Deep Learning

Master Thesis on the course of Forest Information Technology

Thesis written under the supervision of

Prof. Dr. Luis Miranda
Faculty of Forest and environment
Eberswalde, Germany

Prof. Dr. Jan-Peter Mund
Faculty of Forest and environment
Eberswalde, Germany

Eberswalde, 2022

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Podsumowanie

Tytuł: Semantyczna segmentacja martwych drzew (*Picea abies*) z wykorzystaniem uczenia głębokiego

Powierzchnia pokryta lasami i drzewami jest ważnym wskaźnikiem stanu środowiska naturalnego. Lasy borykają się z wieloma trudnościami, które powodują ich zanikanie. Możliwe jest śledzenie stresu fizjologicznego wywołanego przez bodźce biotyczne lub abiotyczne w lasach. Obecnie jednym z głównych problemów jest duża liczba martwych drzew, które bezpośrednio uszkadzają sąsiednie drzewa. W przypadku dokładnego przeglądu dotkniętego obszaru i liczby uszkodzonych drzew można szybko zarejestrować i włączyć do planowania działań w zakresie gospodarki leśnej. Martwe drzewa mogą być odpowiednio identyfikowane przy użyciu metod teledetekcji (RS) i sztucznej inteligencji (AI). W ramach AI opracowano szereg algorytmów segmentacji obrazów, które mogą klasyfikować martwe drzewa z danych RS, takich jak obrazy z bezzałogowych statków powietrznych (UAV). Jeden z algorytmów uczenia maszynowego (ML), Deep Learning (DL), staje się coraz bardziej popularny ze względu na wyjątkową wydajność segmentacji obrazu i różne metody przetwarzania obrazu. Z tej perspektywy, niniejsze badania mają na celu wykorzystanie jednego z modeli DL, sieci U, do segmentacji martwych świerków (*Picea abies*) na ortofotomapach UAV. Sieć została wytrenowana przy użyciu kilku eksperymentów jako testów wstępnych poprzez zmianę rozmiaru piksela, funkcji straty, liczby parametrów, itp. W rezultacie, semantyczna segmentacja obrazu z wykorzystaniem architektury sieci U oraz połączenie odpowiedniej strategii treningowej do wykrywania martwych świerków na ortofotomapach UAV zakończyły się sukcesem. Jednakże model predykcyjny wykazał niewielkie niedopasowanie, które można naprawić poprzez dodanie większej ilości zestawów danych treningowych i modyfikację architektury sieci U. Mimo, że skonstruowany model i dostępne dane zostały wykorzystane do stworzenia bardzo efektywnego wizualnego wyjaśnienia klasyfikacji.

Słowa kluczowe: Semantyczna segmentacja, Deep learning, U-net, teledetekcja, UAV, martwe drzewa.

Summary

Title: Semantic segmentation of dead trees (*Picea abies*) using deep learning

The area covered with forests and trees is an important indicator of the state of the environment. There are multiple difficulties that forests face which cause them to decline. It is possible to track the physiological stress caused by biotic or abiotic stimuli in forests. At present, one of the major problems is the large number of dead trees that directly damage neighbouring trees. If a thorough overview of the affected area and the number of damaged trees can be quickly recorded and incorporated into the planning of forest management measures. Dead trees can be identified appropriately using Remote Sensing (RS) and Artificial Intelligence (AI) approaches. AI has developed a number of image segmentation algorithms that can classify dead trees from RS data, such as unmanned aerial vehicles (UAVs) images. One of the Machine Learning (ML) algorithm, Deep Learning (DL), is becoming increasingly popular due to its outstanding image segmentation performance and various image processing methods. From this perspective, this research aims to utilize one of the DL models, U-net, to segment the dead spruce (*Picea abies*) trees in the UAV orthophotos. The network was trained using several experiments as preliminary tests by altering the pixel size, loss functions, the number of parameters, etc. As an outcome, the semantic image segmentation using U-net architecture and the combination of an appropriate training strategy for dead spruce tree detection on UAV orthophotos were successful. However, the prediction model revealed a minor overfitting, which may be fixed by adding more training data sets and modifying the U-net architecture. Even though the constructed model and the available data were used to produce a very effective visual explanation of the classification.

Keywords: Semantic segmentation, Deep learning, U-net, Remote sensing, UAV, Dead trees.

Zusammenfassung

Titel: Semantische Segmentierung von abgestorbenen Bäumen (*Picea abies*) mittels Deep Learning

Die mit Wäldern und Bäumen bewachsene Fläche ist ein wichtiger Indikator für den Zustand der Umwelt. Die Wälder sind mit zahlreichen Schwierigkeiten konfrontiert, die zu ihrem Rückgang führen. Es ist möglich, den durch biotische oder abiotische Reize verursachten physiologischen Stress in den Wäldern zu verfolgen. Eines der größten Probleme ist derzeit die große Zahl abgestorbener Bäume, die die Nachbarbäume direkt schädigen. Wenn ein gründlicher Überblick über die betroffene Fläche und die Anzahl der geschädigten Bäume schnell erfasst und in die Planung von Waldbewirtschaftungsmaßnahmen einbezogen werden kann. Abgestorbene Bäume können mit Hilfe der Fernerkundung (RS) und der Künstlichen Intelligenz (KI) in geeigneter Weise identifiziert werden. Die KI hat eine Reihe von Bildsegmentierungsalgorithmen entwickelt, die abgestorbene Bäume anhand von RS-Daten, wie z. B. Bildern von unbemannten Luftfahrzeugen (UAVs), klassifizieren können. Einer der Algorithmen des maschinellen Lernens (ML), Deep Learning (DL), erfreut sich aufgrund seiner hervorragenden Bildsegmentierungsleistung und verschiedener Bildverarbeitungsmethoden zunehmender Beliebtheit. Aus dieser Perspektive zielt diese Forschung darauf ab, eines der DL-Modelle, das U-Netz, zu verwenden, um die abgestorbenen Fichten (*Picea abies*) in den UAV-Orthofotos zu segmentieren. Das Netz wurde in mehreren Experimenten als Vorversuch trainiert, wobei die Pixelgröße, die Verlustfunktionen, die Anzahl der Parameter usw. verändert wurden. Das Ergebnis war, dass die semantische Bildsegmentierung unter Verwendung der U-Netz-Architektur und die Kombination einer geeigneten Trainingsstrategie für die Erkennung abgestorbener Fichten auf UAV-Orthofotos erfolgreich waren. Das Vorhersagemodell wies jedoch eine geringfügige Überanpassung auf, die durch Hinzufügen weiterer Trainingsdatensätze und Änderung der U-Netz-Architektur behoben werden kann. Obwohl das konstruierte Modell und die verfügbaren Daten verwendet wurden, um eine sehr effektive visuelle Erklärung der Klassifizierung zu erstellen.

Schlüsselwörter: Semantische Segmentierung, Deep Learning, U-Netz, Fernerkundung, UAV, tote Bäume.

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I. INTRODUCTION

Forests are an important resource and cover about one-third of the earth's surface (Keenan et al. 2015). According to Trumbore, Brando, and Hartmann (2015) all living things rely on forests to provide products and amenities for society including timber, paper, firewood, wildlife habitat, carbon storage, and recreational services. Forests provide wildlife habitat and livelihoods for people, protect watersheds, prevent soil erosion, and mitigate climate change (Trumbore et al. 2015). Forests face many threats and stressors, including deforestation (Ferrer Velasco et al. 2020), drought (Süßel and Brüggemann 2021), climate change (Prietz et al. 2020), air pollution (Rathmann et al. 2020), bark beetle disturbance, mortality from a forest fire and unsustainable management (Foley et al. 2005).

Forest management is crucial for ensuring the efficiency that can meet the earth's population requirements. The development of new sensors and policies provides opportunities to expand traditional practices by combining remotely-sensed data products to deliver improved statistics on the condition of forests (Estoque et al. 2021). Since the initiation of earth-observation satellites, which are appropriate for monitoring the vegetation, researchers have used images to quantify the spatial extent of insect eruptions and mortality of the tree at regional and landscape scales using fine resolution images approximately 30m (Bright et al. 2020). Recently, researchers have introduced the usage of high-resolution (≤ 5 m) satellite imagery and images collected from Unmanned Aerial Vehicles (UAVs) for monitoring tree health (Schiefer et al. 2020). As an Artificial Intelligence (AI) tool for analyzing RGB images, Deep Learning (DL) has become increasingly powerful. Recently, DL techniques have been used to detect trees (Chadwick et al. 2020; Ocer et al. 2020), categorize tree species (Egli and Höpke 2020; Kentsch et al. 2020; Tran et al. 2020), and detect forest disturbances such as insect infestations or wildfires (Safonova et al. 2019). Diez et al. (2021) mentions that the research field of DL, which is a part of machine learning, has proliferated in recent years. DL can produce proficient observations on every single tree in hundreds or thousands of hectares (Diez et al. 2021)

There are many problems that affect the health of the forest. One of the reasons is the negative influence of neighboring dead trees near healthy trees (Ciesla and Donaubauer 1994). The primary goal of this study was to use DL to identify those dead trees. In the

detection of dead trees, segmentation plays an important role in various applications and presents a challenging problem for computer vision (Minaee et al. 2021; Yuan et al. 2020). Several algorithms have been developed to segment images using AI (Niazi, Parwani, and Gurcan 2019). Many of the aforementioned scholars believe that DL is becoming increasingly popular for image segmentation. It has developed many image processing techniques and achieved exceptional results in image segmentation (Mazza et al. 2019; Wagner et al. 2019). Image segmentation is based on constructing neural networks with many hidden layers and is commonly known as DL models (Chen et al. 2018; Krizhevsky, Sutskever, and Hinton 2017). DL models are intensively used to identify forest dead trees because it provides greater accuracy than conventional methods (Kattenborn et al. 2020).

1. Scope of the thesis

Germany is one of the most densely forested countries in Europe and a one-third of land is covered by forest (Welle, Sturm, and Bohr 2018). In this study the area called Haselberg near Prötzel (Figure 1) is belongs to Brandenburg state. The study area has been managed by the Eberswalde University for Sustainable Development (HNE) since 2019. In January 2020, during a forest inspection which was done by bachelors' students in the HNE, it was found that the forest had many dead trees. Spruce (*Picea Abies*) was the most affected tree species. One of the biggest problems at present is the large number of dead trees directly damaging neighboring trees. If a detailed assessment of the affected area and the number of damaged trees can be immediately recorded and included in the planning of forest management measures. In forest management, several approaches can determine the forest's condition. The main objective of this research is to identify dead trees in forests using UAV orthophotos. To summarize, this master's thesis presents semantic segmentation of dead trees (*Picea abies*) using DL with the UAV orthophotos.

The specific objectives of this research have been narrowed down as follows:

1. To perform semantic segmentation of dead trees (*Picea abies*) using DL with the UAV-orthophotos.
2. To predict UAV orthophotos with different resolutions from the developed model.

2. Study Area

The study area is on the western edge of Prötzel on the hills of the Steinberg, which Bussemer (2005) argues probably belongs to the Frankfurt glacial margin. This small chambered, lowland landscape on the watershed between Berlin and Eberswalde consists of various glacial sediment types with a predominantly sandy character (Bussemer 2005). It is located in Brandenburg's federal state with 52.724430 North and 14.003200 East, is closely related to the highly urbanized German capital Berlin (Ihinegbu and Ogunwumi 2022) (Figure 1).

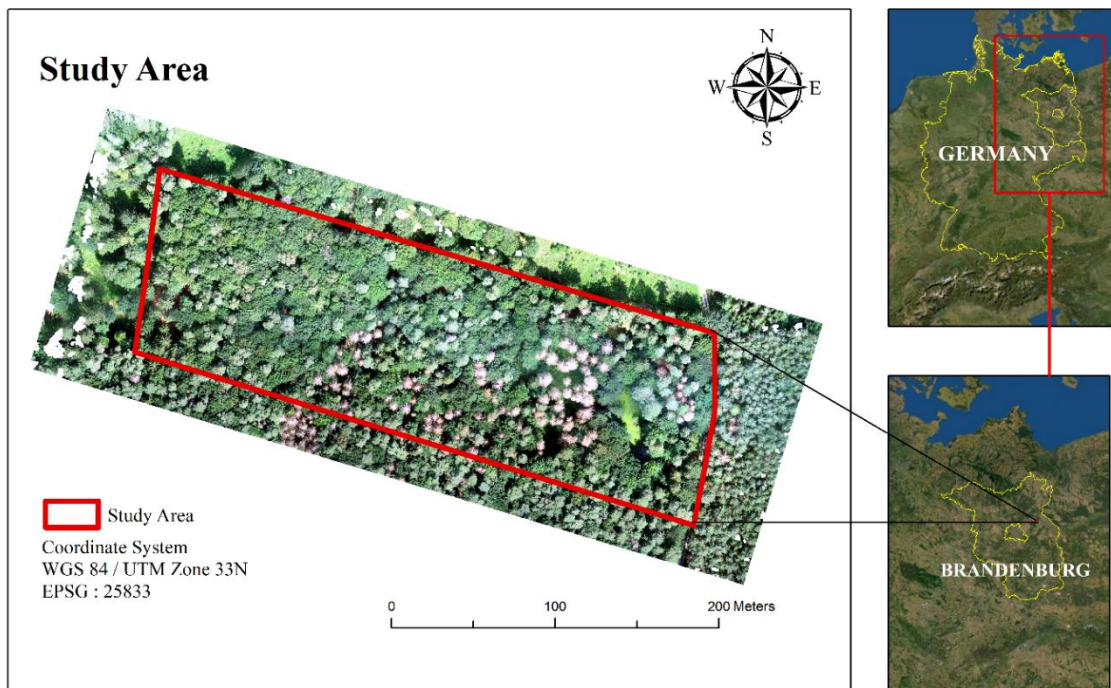


Figure 1: Study area

3. Limitation and Assumptions

The major limitation to achieving the research objectives is the available data. Ideally, this research would produce a DL model that detects dead spruce trees with 95% accuracy. However, there was not enough data currently available at different spatial resolutions and locations to accomplish this goal. The lack of data also means that very few aerial datasets are available for training the DL model. Moreover, this research is developing a model to predict dead trees only using the discoloration and shapes of the crown or leaves.

II. REVIEW OF THE LITERATURE

This chapter provides a technical overview of information on the forest health and dead trees, Remote Sensing (RS), and semantic segmentation. This will be accomplished by reviewing forest health classes, RS datasets, AI and their application to the image classification problem, and a convolutional neural network (CNN) variant known as the U-Net. This section will also explore metrics, loss functions, and their role in final segmentation results.

1. Factors to identify forest health

Forest health depends on conditions of individual trees; which is a significant factor in forest management (Safe'i et al. 2021). Many factors indicate the health of the trees including among others vegetation, crown condition, defoliation, discoloration (Morelan 1994). In this research, the vitality range is determined based on needle loss and percentage of discoloration, as shown in Table 1 and Figure 2 (Innes 1990).

Table 1: Classification of forest damage based on needle loss and chlorosis(Innes 1990; Uhlmann et al. 1989)

Damage Class	Vitality	Needle loss (%)	Discoloration (%)
0	Healthy	0-10	0-25
1	Slight damage	11-25	0-10% of needles
2	Moderate damage	26-60	26-60% of needles
3	Severe damage	61-99	61-99% of needles
4	Dying	100	Dead trees

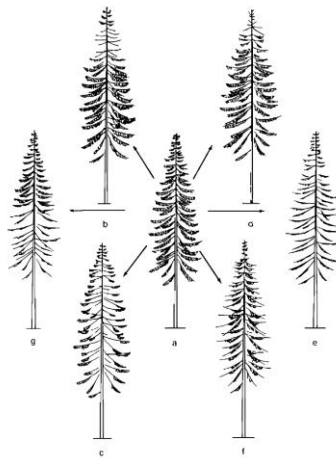


Figure 2:Defoliation types in spruce, a. none; b. small window; c. large window; d. top only; e. uniform; f. peripheral; g. bottom-up (Innes 1990)

2. Remote sensing in Forestry

To identify the forest health, RS data are widely used (Lausch et al. 2017). RS consists of observing electromagnetic radiation that is emitted or reflected from distant objects and captured by some kind of sensors (Kennedy et al. 2009). The use of aerial imagery for forestry applications has been around for decades, including mapping cover types, detecting damage to trees, and stand delineation (Cielsa 2000). To assess forests and analyze the effects of various stressors on forests, a system that uses terrestrial in situ observations and remote sensing technologies is critical (McDowell et al. 2015; Trumbore et al. 2015; Wingfield et al. 2015). Monitoring forest health can be done with several RS applications (Pause et al. 2016). In addition, one of the DL methods, namely semantic segmentation, is used to detect dead trees based on RS data, especially from satellite and UAV data (Jiang, Yao, and Heurich 2019).

2.1 Satellite data

Several large data archives (e.g., Landsat) have made RS data archives available to the public in recent years which has led to greater development of RS technologies and applications (Wulder et al. 2012). It also includes entire space missions developed for the public (e.g., the European Space Agency's (ESA) Sentinel missions) (Majasalmi and Rautiainen 2016) and the development of open-source tools for the processing of RS data. It is expected that these developments will lead to a tremendous push in the use of satellites to understand forest health (Wulder and Coops 2014).

2.2 UAV data

UAVs have proven to be a useful source of data for many forest management situations (Dash et al. 2016). In recent years there have been a rising number of studies looking at how UAVs can be used for forest monitoring in a wide range of applications including surveying forests (Goodbody et al. 2017; Miller et al. 2017; Puliti et al. 2017), Providing information on silvicultural practice (Watt et al. 2017), monitoring of forest health (Cardil, Vepakomma, and Brotons 2017; Michez et al. 2016), and natural hazard events such as forest fires (Cruz et al. 2016; Yuan, Liu, and Zhang 2017), wind damage (Mokroš et al. 2017), and harvesting operations.

3. Artificial intelligence

It is necessary to understand AI in order to solve environmental conditions (Yi 2020). AI is about developing intelligent machines from large amounts of data that learn from experience and perform human-like tasks (Duan, Edwards, and Dwivedi 2019). This covers both ML and DL, as well as applications that use algorithms to perform intelligent tasks.

3.1 Machine Learning

The field of ML is described as one that enables computer systems to automatically improve their performance over time. Although specialized learning methods now exist, scientists strive to create more broadly applicable systems with more powerful learning capabilities (Alzubi, Nayyar, and Kumar 2018; Mitchell 1997). The application of ML teaches computers how to handle data more effectively. The whole purpose of machine learning is to learn from the data (Batta 2020).

3.2 Deep learning

DL is a branch of ML that helps to expand the scope of ML techniques by learning multiple recursive layers of data representation. The depth of the model is made up of more than one recursive layer opposed to standard ML techniques. DL must be used in combination with neural networks to learn the many different features and representations of the data (Pouyanfar et al. 2018). DL enables computer models consisting of multiple processing layers to learn data representations with multiple levels of abstraction. These methods have improved state of the art image classification, speech, visual and object recognition, and many other areas such as drug discovery and genomics (Lecun, Bengio, and Hinton 2015).

4. Neural networks

Neural networks consist of layers stacked on top of each other. Each layer filters the input data to learn a final representation useful for a particular purpose (Bashivan et al. 2016).

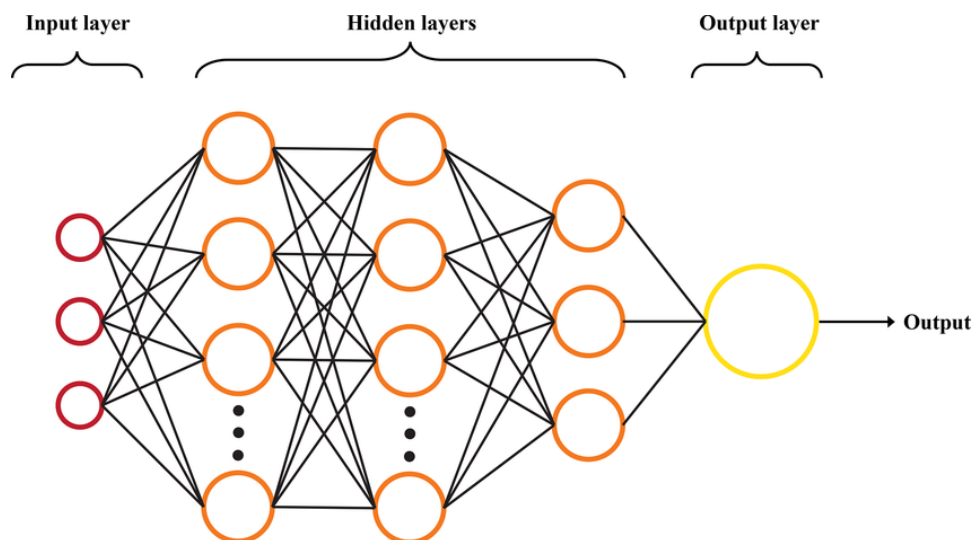


Figure 3: An artificial neural network (ANN) diagram. (Vassallo, Krishnamurthy, and Fernando 2020)

There are four components to training a neural network:

- Input data
- Layers
- Loss function
- Optimizer

In a neural network, an input layer passes the data, usually in the form of a multidimensional vector, to the input layer, which passes it on to the hidden layers (O’Shea and Nash 2015). Yi (2020) states that layers are the fundamental data structure of a neural network. He also states that each layer processes inputs and outputs in data containers called tensors, and that layers also have values called weights. First, to train a neural network is to calculate the correct values for these weights (Yi 2020). Then the loss functions are used to control the error between the output of the algorithms and the specified target value (Christoffersen and Jacobs 2004; Vassallo, Krishnamurthy, and Fernando 2020). Lastly the optimizer uses the desired results as a feedback signal. The optimizer uses a Backpropagation algorithm to change the weights of the network layers (Zhang et al. 2007).

4.1 Convolutional Neural Networks

CNNs are similar to traditional Artificial Neural Networks (ANNs) in that they consist of neurons that optimize themselves through learning (Indolia et al. 2018). CNNs are

commonly implemented for image analysis because they have particular characteristics that make it simpler to recognize patterns within images. CNN assumes that the input consists of images and that the weights and biases of the neurons can be learned (Sahiner et al. 1996; Yadav and Jadhav 2019). Each neuron receives an input and performs an operation, and the only notable difference between CNNs and traditional ANNs is that CNNs are mainly used in the field of pattern recognition in images. This allows us to encode image-specific features into the architecture, making the network more suitable for image-oriented tasks - while further reducing the parameters required to build the model (Alom et al. 2019; O’Shea and Nash 2015).

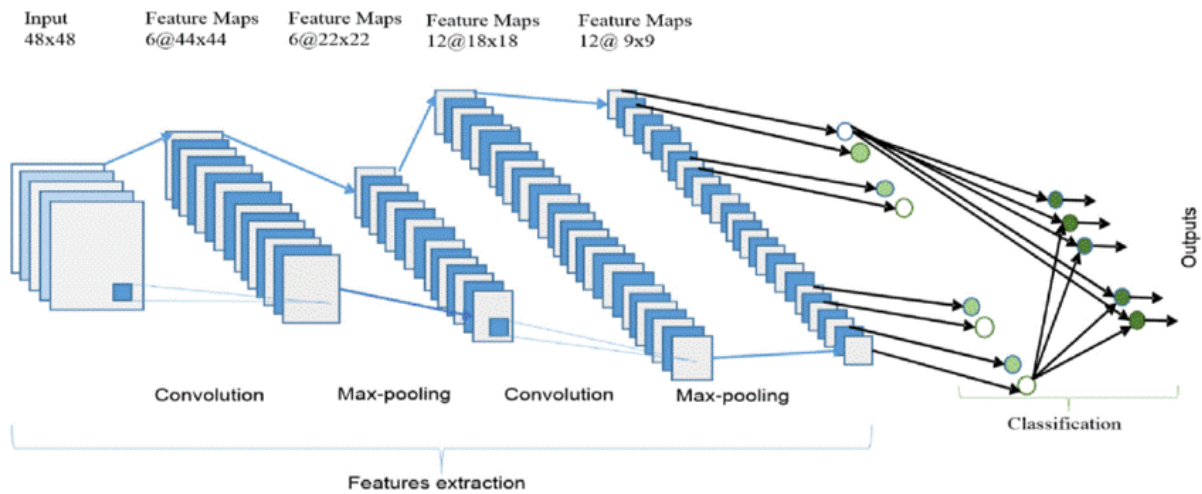


Figure 4: The overall architecture of the CNN (Alom et al. 2019)

4.1.1 Convolution

The purpose of the convolution layer is to extract patterns found in local regions of the input images that are quite common in natural images. Convolution is a process that creates a new function from two functions of a real-valued argument. Assume that the input position function $x(a)$ is based on the age of the measurement a , the output estimate function $s(t)$ is based on time t , the weighting function $w(a)$ favors the most recent measurements, and the input position function $x(a)$ is based on time t . With these specifically defined functions from (Goodfellow, Bengio, and Courville 2016), the general formula for convolution is.

$$s(t) = \int x(a)w(t - a)da \quad (1)$$

In CNNs, the weighting function $w(a)$ is known as the kernel, the output $s(t)$ is known as the feature map, and the function $x(a)$ is known as the input (Baskin et al. 2018; Goodfellow et al. 2016).

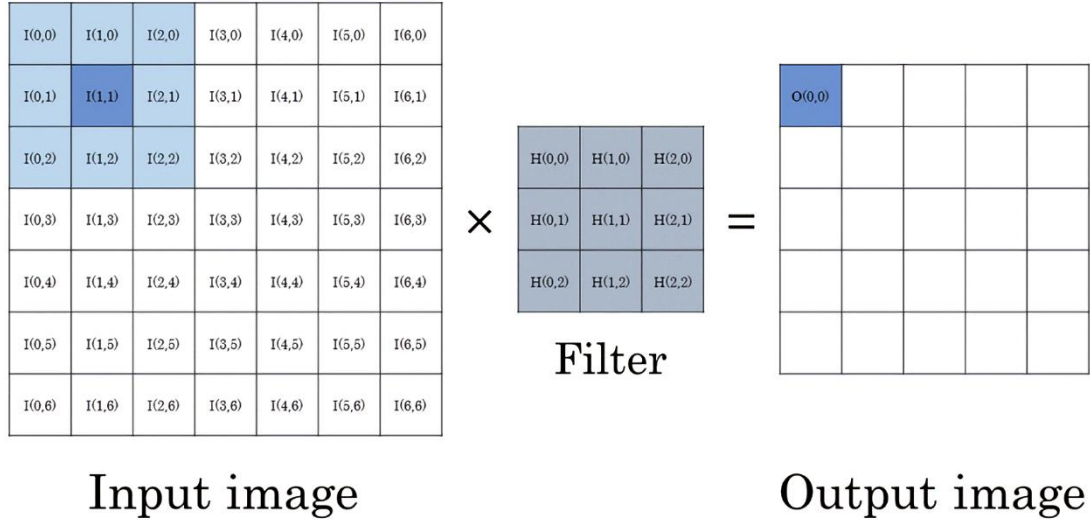
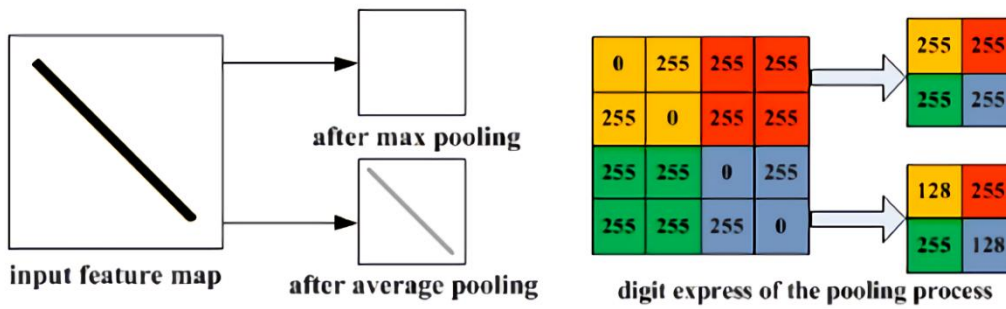


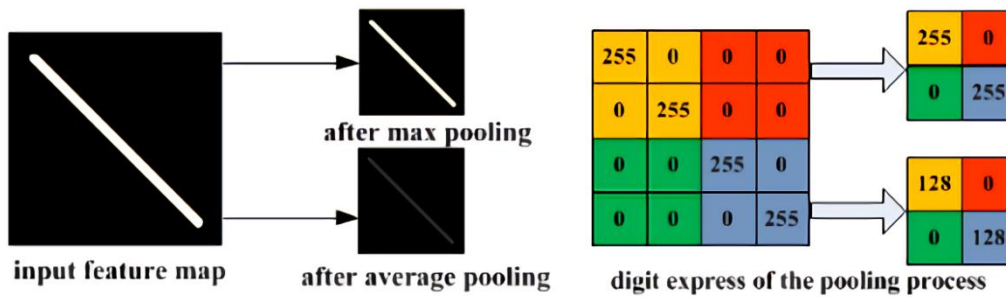
Figure 5: Visual representation of an image convolution with an input image of size 7×7 and a filter core of size 3×3 (Baskin et al. 2018)

4.1.2 Max-Pooling

The max-pooling and average-pooling methods are two popular methods used by CNNs due to their computational efficiency. For example, the Average-Pooling method is used in(Jarrett et al. 2009), which achieves excellent image classification accuracy on the Caltech101 dataset. In (Krizhevsky, Sutskever, and Hinton. 2012), the max-pooling method is successfully applied to train a deep “convnet” for the ImageNet competition. Although these two types of pooling operators can work very well on some datasets, it is still unknown which one is more suitable for solving a new problem. In other words, choosing the pooling operator is a kind of empiricism. However, the average-pooling and max-pooling operators each have their own disadvantages. The other items in the pooling zone are ignored when using max-pooling, which only considers the maximum element. Sometimes, this produces an unacceptable outcome(Yu et al. 2014).In this thesis, max pooling was used as a pooling operator.



(a) Illustration of max pooling drawback



(b) Illustration of average pooling drawback

Figure 6: Toy example illustrating the drawbacks of max pooling and average pooling (Yu et al. 2014)

4.2 Semantic Segmentation

Semantic segmentation is an image classification technique in which each pixel of an image is provided a corresponding class label (Fu and Mui 1981). It has abundant applications in computer vision and AI, which include autonomous driving, robot navigation, industrial inspection, and remote sensing; in cognitive sciences and computer science - detection of conspicuous objects; in agricultural sciences; in fashion - categorization of clothing. In medical sciences - analysis of medical images, etc. Previous approaches to semantic segmentation include textonforest, random-forest-based classifiers, and others. DL techniques enable precise and much faster segmentation (Artacho and Savakis 2019; Lateef and Ruichek 2019). Segmentation in aerial imagery is often performed with Fully Convolutional Networks (FCNs) and U-nets.



Figure 7: An application of semantic segmentation (Artacho and Savakis 2019)

4.3 Fully Convolutional Networks

A CNN-based variant, known as FCN, represents one of the most significant developments in image segmentation (Maraci et al. 2020). The fully associated layers at the end of the traditional CNN into convolution layers by the FCN. This results in a network that computes a nonlinear filter for the output vectors of each layer. Thus, the final network can process an input of any size and provide an output with the correct spatial dimensions (Sharma, Patel, and Bishnu 2017). Therefore, the classification network can output a graph of the selected object class. An effective machine for dense end-to-end learning is created by further modifying the framework by adding layers and a spatial loss (Long, Shelhamer, and Darrell 2015).

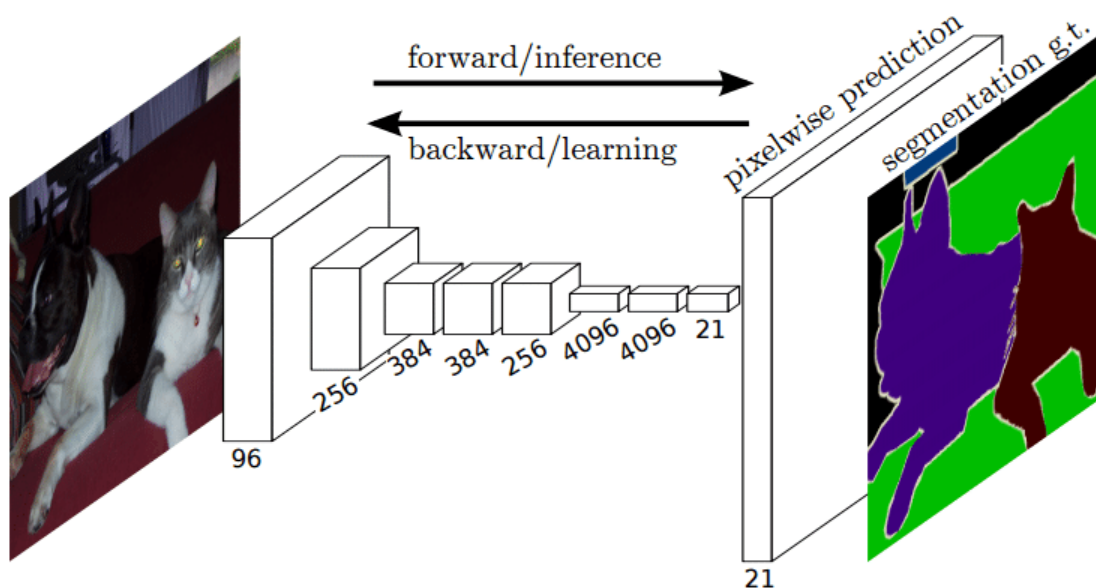


Figure 8: An illustration of FCN (Sharma, Patel, and Bishnu 2017)

4.4 U-Nets

The U-net architecture is a variation of an FCN, most commonly used for the task of semantic segmentation. The original U-Net architecture was developed by (Ronneberger, Fischer, and Brox 2015) to perform image segmentation and localization for biomedical purposes. It has been used to classify different regions of microscopic histology slides into different cell structures. The U-net architecture responds to shapes and textures in small regions and at different scales, resulting in a pixel-by-pixel analysis of the input images. A U-net variant is shown in the demonstration by (Zhang, Liu, and Wang 2018) for delineating roads in high-resolution satellite imagery. According to Ronneberger et al. (2015), U-networks can be trained with much less training data (within their specific problem domain) than some other approaches seem to require.

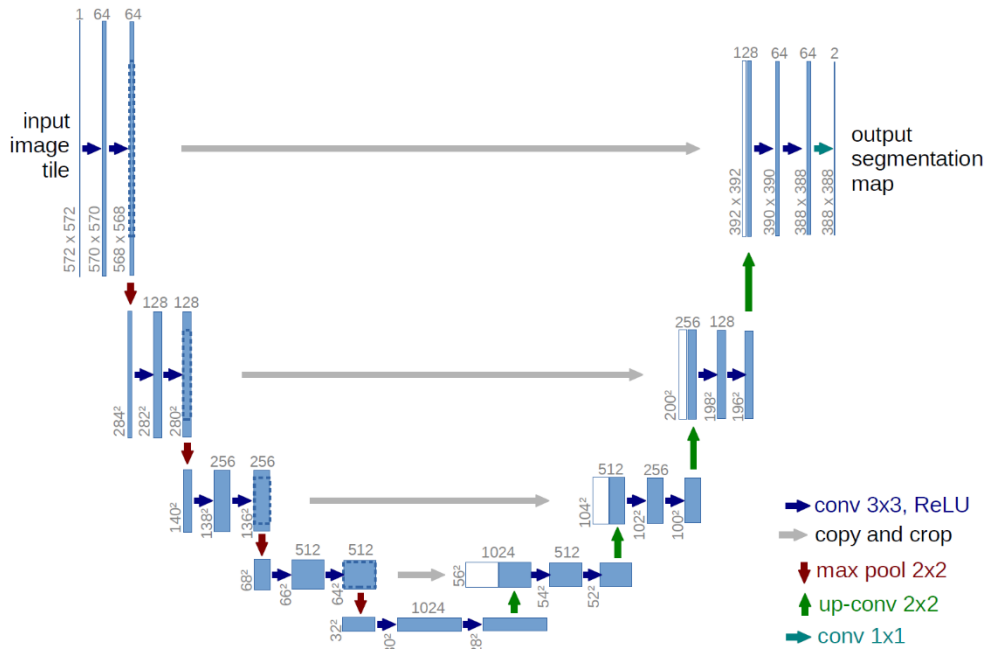


Figure 9: The U-Net diagram (Ronneberger et al. 2015)

4.5 Evaluation Metrics

To estimate the effectiveness of different network topologies for semantic segmentation, an appropriate metric that accurately describes the network's ability to recognize a class is required. In this study, initial experiments were conducted and various metrics were used to verify the working of the model.

The simplest method for evaluating the overall accuracy of image classification is to examine pixel accuracy. It is done by calculating the percentage of pixels in a test image

that were correctly detected (Congalton 1991). There are numerous terms that are often used along with the description of accuracy: true positive (TP), true negative (TN), false negative (FN), and false positive (FP) (Zhu, Zeng, and Wang 2010).

Accuracy: measures how many observations, both positive and negative, were correctly classified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Another way of calculating accuracy is the F1Score: Measures the harmonic mean between Recall and Precision (Alfonso Francia et al. 2020)

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$F1Score = \frac{2 * TP}{2 * TP + FP + FN} \quad (5)$$

The Jaccard index is an alternative performance metric that is employed to combat the unreliable measurement of accuracy of the prior method. The Intersection over Union (IoU) is another name for this metric. The similarity between the predicted region and the actual region for an object in a sequence of images is calculated using this metric.

$$Jaccard = \frac{TP}{TP + FP + FN} = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \quad (6)$$

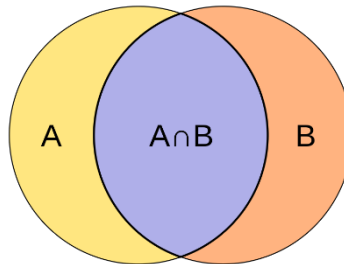


Figure 10: Visual representation of the Jaccard index, where A is the ground data and B is the output prediction for a single class (Yi 2020)

4.6 Loss Functions for Segmentation

There are several loss functions for this segmentation task that are comparable to the evaluation measures used to more accurately assess the effectiveness of a model. In this research, several loss functions were used to determine the best function for this problem solution, which are explained below.

In binary cross entropy (BCE), each projected probability is scored against the actual class outcome, which can be either 0 or 1. Then the score is determined by reducing the probabilities according to how far they are from the expected value. More specifically, how close or how far the value is from the actual value.

$$BCE = \sum_{x \in \Omega} w(x) \log(p^{\ell(x)}(x)) \quad (7)$$

Another loss function is the Jaccard's loss function or IoU. The calculation of IoU in (6) assumes that the output prediction mask consists of 1s and 0s. However, the actual output of neural networks consists of a set of probabilities that represent the probability with which the network predicts that a pixel belongs to a certain class.

$$IoU = \frac{|T * P|}{|T + P - (T * P)|} = \frac{I}{U} \quad (8)$$

where T is the truth data for an image and P is the prediction mask of the same image.

One of the other loss function used by (Reder et al. 2022) for a semantic segmentation of windthrown trees is F1CrossEntropyLoss. The loss function "BCE", which is suitable for binary classification tasks, was modified by adding the difference between the F1Score and 1 to better represent the training success.

$$F1CrossEntropyLoss = (1 - F1Score) + BCE \quad (9)$$

III. MATERIALS AND METHODS

The following chapter describes the data collection, creation of the training dataset, the alterations to the U-Net architecture, and the training, evaluation, and testing of the models.

1. Workflow

The workflow depicted in Figure 11 comprises four sections: Data collection, Input data, Preparation of data set, and Training and evaluation of the neural networks (Section 2-6). For a detailed description of the network architecture used, see Figure 18.

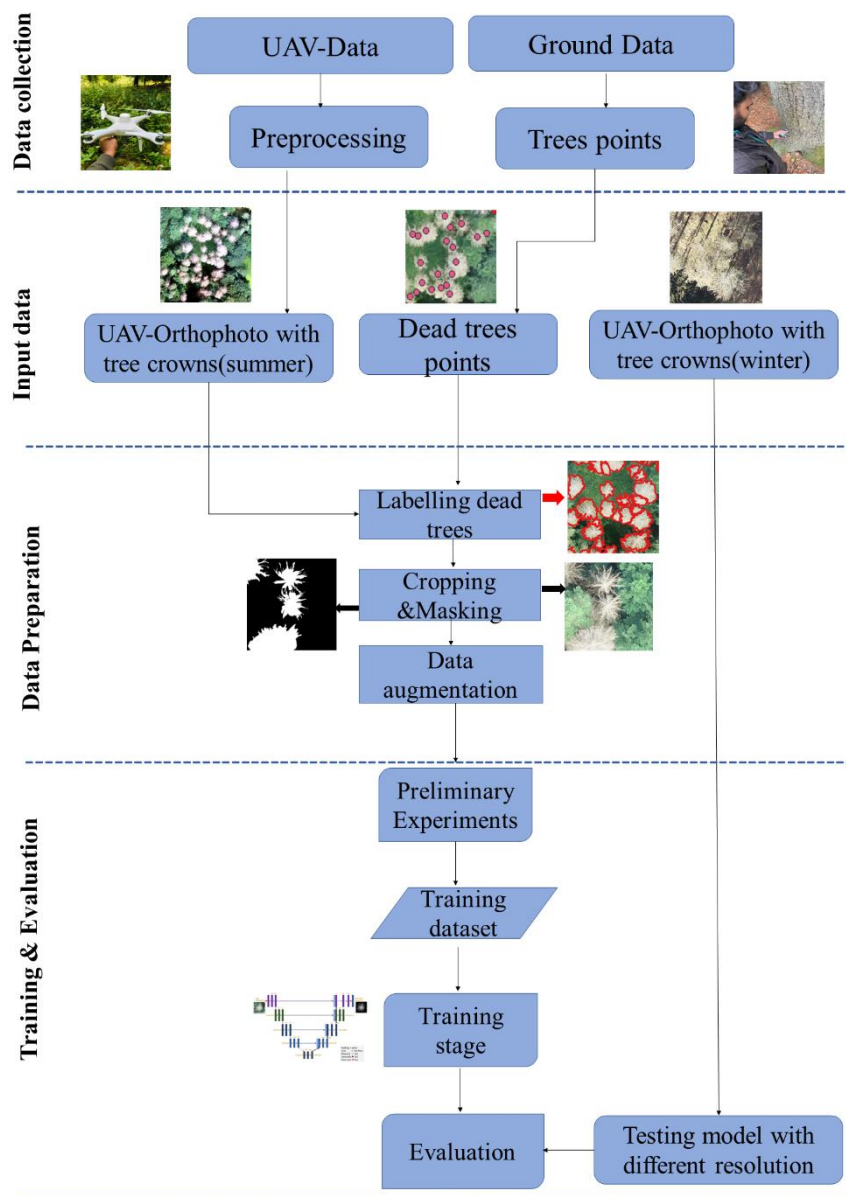


Figure 11: Workflow diagram

2. Data collection

The dead tree classification was conducted using ground truthing and UAV datasets. The following sections describe the data collection procedure in detail.

2.1 In situ data

As an initial inventory, the reference data for the tree species analysis was gathered in the Prötzel forest in January 2020 with bachelor students from HNE. It found nine different species of trees in this forest, with spruce being the species with the highest percentage of dead trees.

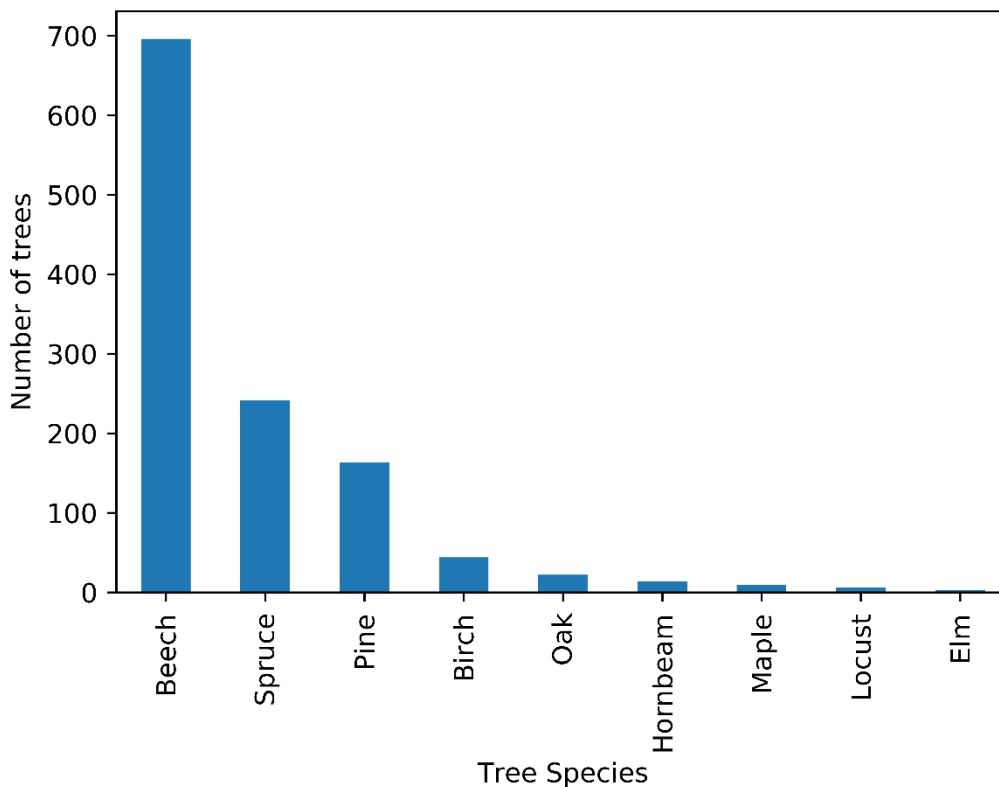


Figure 12: Number of trees with species in Prötzel based on 2020 forest inventory data.

The spruce (*Picea abies*) was found to be the highest dead tree after the initial data collection. Therefore, a separate survey was conducted during the first week of October 2021 to determine the number of dead trees by their vitality classes based on crown condition (Innes 1990). The vitality of spruce trees was classified into five classes from 0 to 4. During the surveys, the information was recorded in the form of height, DBH (Diameter Breast Height), GPS points, and vitality classes (Uhlmann et al. 1989).

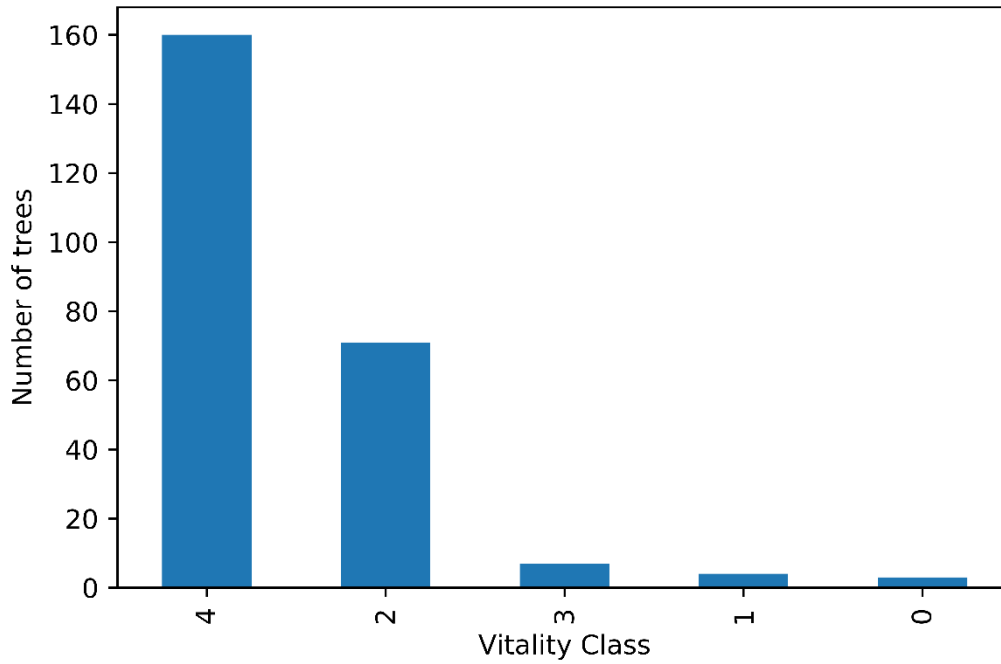


Figure 13: Vitality classes of spruce in Prötzel based on forest inventory data 2021.

From Figure 12 and 13, the total number of spruce trees is 247, and 159 trees belong to dead trees.

2.2 UAV based Orthophotos

The forest area was captured on July 21, 2021, using a DJI Phantom 4 RTK quadcopter with an RTK controller. The university also conducted other flights in March 24, 2022 using a DJI Phantom 4 RTK with a different spatial resolution as a general seasonal flight. This research also used these data to evaluate and predict the model. The specifications of the two UAV orthophotos are shown in the Table 2.

Table 2: Details on the UAV data used in the study

Specifications	DJI Phantom 4 RTK	DJI Phantom 4 RTK
Acquisition date	21-06-2021	24-03-2022
Spatial resolution	1.73 cm	3.45 cm

3. Input data

3.1 UAV-Orthophotos

The raw images were imported into Agisoft Meta shape, which is a photogrammetry pipeline tool. A digital surface model (DSM), digital terrain model (DTM), crown height model (CHM), and the point cloud were created. The point cloud was used to create the orthomosaic. The 2021 orthomosaic was used to train the model, and the 2022 orthomosaic was used to verify the final model prediction with different resolutions. The use of orthomosaics rather than UAV raw data is recommended since geo-referenced images allow for the precise position and subsequent quantification of the detected trees.

3.2 Dead trees points

Due to the GPS correction, the spruce tree points were not geo-referenced on the trees. The first step was to make geo-referenced points with the UAV orthophoto. This was done using the vertex tool option in the toggle editing in QGIS 3.26.0-Buenos Aires. The dead tree 141 tree tops visible in the 2021 UAV orthomosaic were then applied for initial labeling.



Figure 14: Points (a)before and (b)after the geo-reference

4. Data Preparation

The following section describes the preparation of the data sets used for training and evaluation. The different types of preparation strategies are described, and these processes were performed using QGIS, R, and Python programming languages.

4.1 Initial Labelling

All 141 dead trees were manually outlined by digitizing polygons. Due to the crown's form, this process was particularly challenging. It was very difficult to detect the edges of the crown. The specific labeling is utilized to produce the mask.

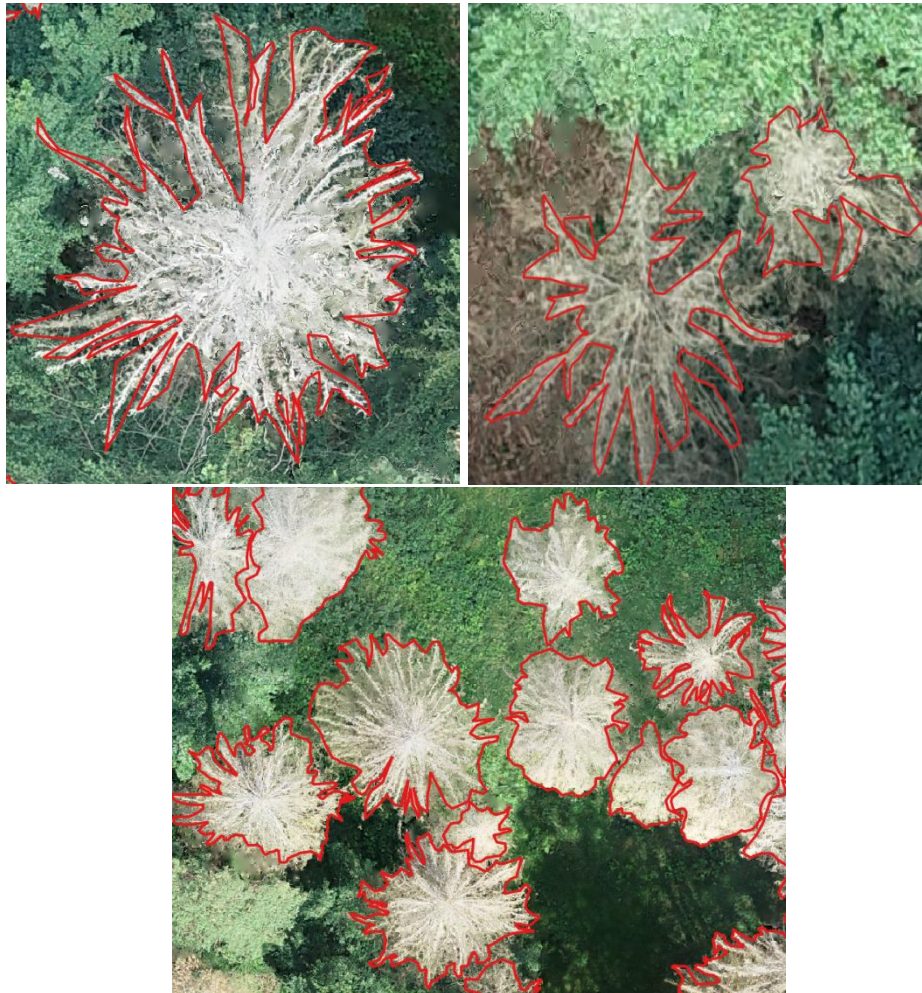


Figure 15: Example data sets after labelling

4.2 Cropping and masking

After labeling, the polygons were cropped and masked. For this purpose, the center of each polygon was selected, and from that point, squared image tiles with the side length of 12 m were clipped, which consists of 685 x 685 pixels.

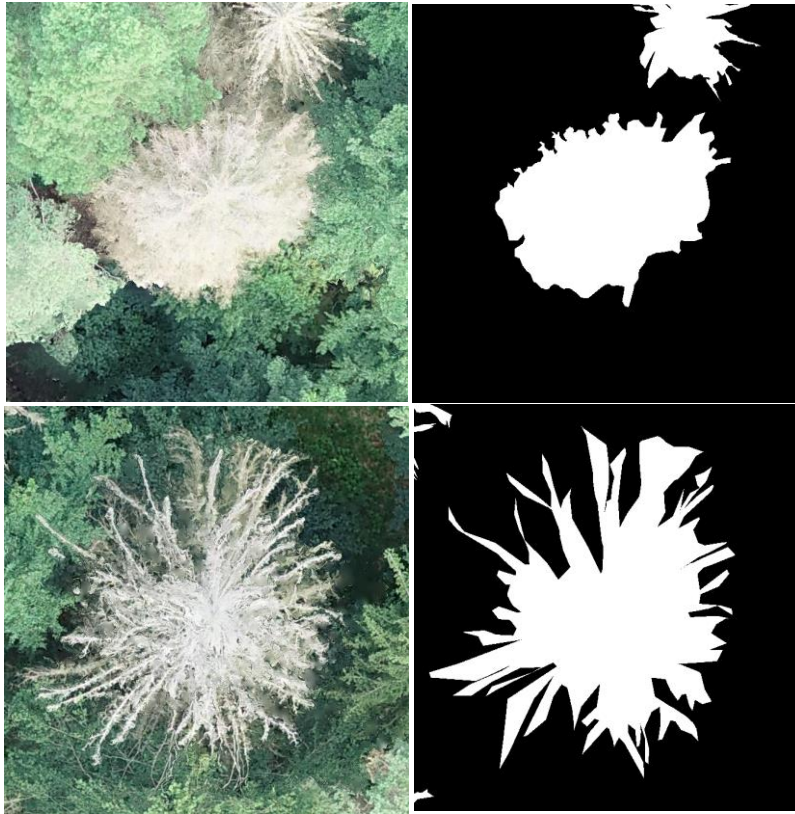


Figure 16: Two sample data sets after cropping and masking

4.3 Data augmentation

Data augmentation techniques in data analysis involve adding slightly modified copies of existing data or creating entirely new synthetic data from existing data (Shorten and Khoshgoftaar 2019). Rather than using the 141 samples used for training and validation, a data augmentation procedure was utilized to build slightly different copies for each tree canopy in order to produce more training datasets that typically represent the properties of dead tree canopies. For this purpose, a library called albumentation was used. In albumentation the original tree crowns were augmented in six different ways.

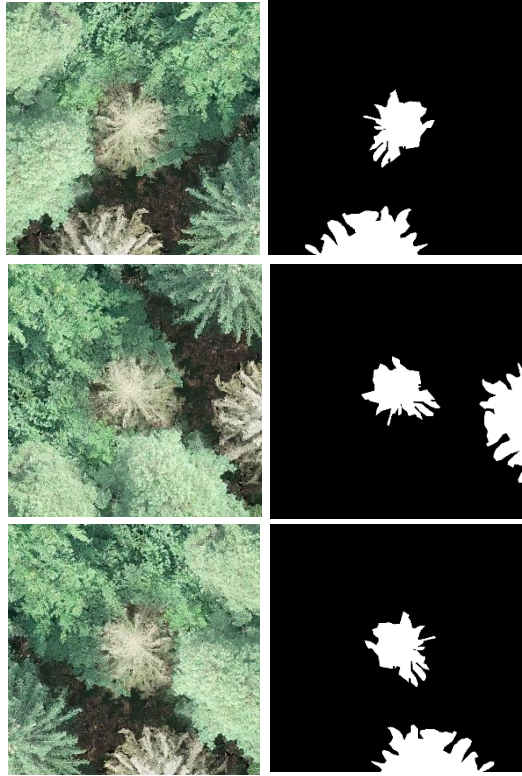


Figure 17: Diagram of the augmentation process of a sample training dataset

5. Preliminary Experiments

In the initial phase, many experiments were conducted which is necessary to obtain the working model. These experiments helped to determine the best working model for dead spruce detection. The experiment first tried to train the model with segmentation models, which are neural network libraries for image segmentation based on the Keras (TensorFlow) framework using different image sizes of 128×128 , 256×256 , and 512×512 . The loss function was modified using all the types of loss functions listed in Table 3. Unfortunately, these experiments did not give good results in dead tree segmentation with this dataset.

The next model used was from the original U-Net research paper (Ronneberger et al. 2015), modifying the same as used in the models above. In both cases, 987 datasets were used. The best results were obtained in these models are shown in the final results. The loss function used was BCE and accuracy as a metric with 512×512 input size.

Table 3: The preliminary experiments with the parameters used. (Bolded are the best)

Model	Training datasets	Input size	Loss function	Metrics
		128 × 128		
Segmentation models	987	256 × 256		
		512 × 512	BCE, IoU, F1CrossEntropyLoss	Jaccard, F1Score, Accuracy
		128 × 128		
U-net	987	256 × 256		
		512 × 512		

6. Training and Evaluation

This section includes detailed information about the training datasets, modified network architecture, hardware and software used, and other training and evaluation methods.

6.1 Training Datasets

The total number of images and masks after image augmentation was 987. The datasets were 685 × 685 pixels and were resized to 512 × 512 pixels in the Cv2 library. 80% of the datasets were split to training size and 20% to testing and validation using `train_test_split` in `sklearn.model_selection`.

6.2 Model Architecture

The U-Net architecture presented by (Ronneberger et al. 2015) was selected for the semantic segmentation of the UAV images and adapted to the specific requirements (Figure 18). The adapted U-net architecture consists of a contracting branch (encoder) and an expanding branch (decoder), distributed over 5 layers. The input layer has a size of 512 × 512 pixels and 3 feature layers, one for each RGB channel. Each layer in the encoder contains two convolutional layers with a kernel size of 3 × 3 pixels and a max-pooling layer with a pool size of 2 × 2 pixels and a stride of 2 pixels. Each contraction step to the next layer doubles the number of features (16, 32, 64, 128, 256) and decreases their resolution to 256 × 256, 128 × 128,.....32 × 32. The decoder mirrors the encoder, but the max-pooling layer is replaced by a 2 × 2 convolutional layer that halves the number

of features and samples up the layer's resolution, inverting the operation in the contracting branch, followed by a concatenation with the corresponding layer.

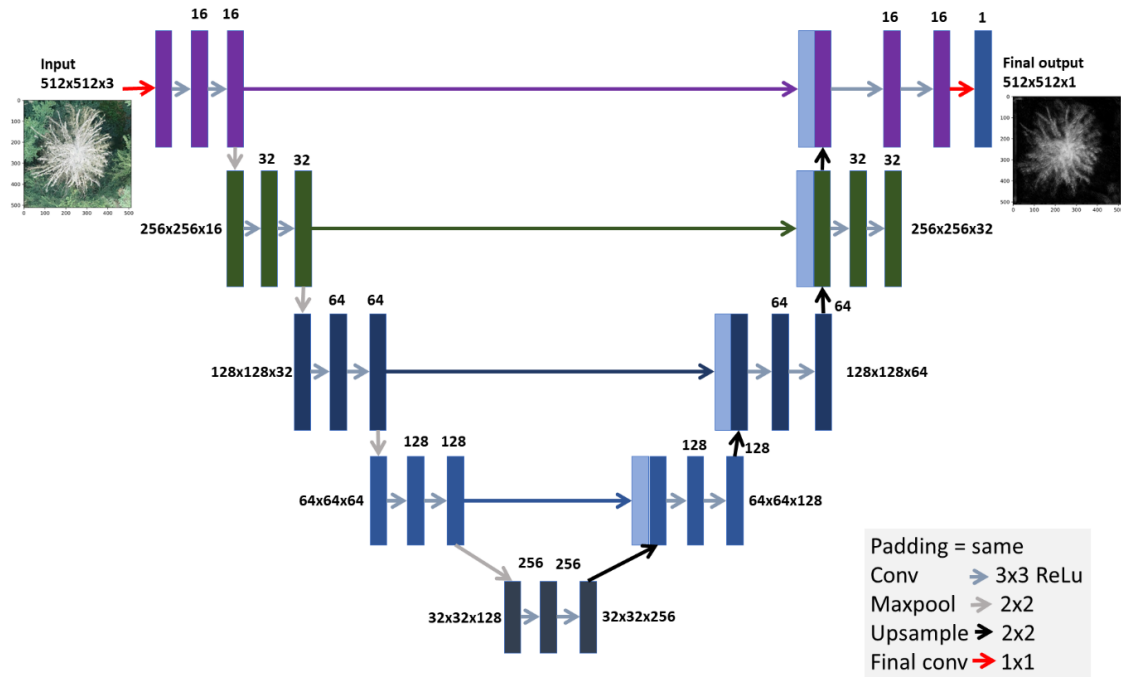


Figure 18: U-net architecture with a decoding and encoding branch that uses skipping connections between the relevant levels. The number of features and the size of the input (left) and output (right) are shown below the layers, respectively

The hidden layers contain rectified linear units (Relu) to avoid disappearing gradient problems (Lau and Lim 2019). In the output layer, the Relu activation function was used to determine the probability that a pixel represents a tree crown (Safonova et al. 2019). In total, the network consists of 1,97676 trainable and 0 untrainable parameters. The ADAM optimizer was adapted to fit the model, as this optimizer is designed to handle large datasets with multiple features and has no memory requirements (Kingma and Ba 2014). The loss function BCE, appropriate for binary classification applications, was chosen with the accuracy metrics. Callbacks were introduced to reduce learning when the loss was stable for 2 epochs to avoid learning plateaus and to terminate learning early when loss did not improve for 4 epochs.

6.3 Training stage

Proper initialization of model weights is critical to training success, as poorly initialized models are unlikely to converge, even with a sophisticated optimizer (Le, Jaitly, and Hinton 2015). This is especially important when only a few training examples are available. One approach to overcoming this problem is to use pre-trained networks and to apply transfer learning from them. In this study, the initial training was performed with the original datasets containing 141 images and corresponding masks. However, since the datasets were very small, the augmentation datasets were trained with 900 datasets, so the pre-trained network approach was not adopted based on the results in the augmented training datasets.

6.4 Evaluation

To evaluate the classification performance, the accuracy of the pixels was checked, and the randomly selected tiles were also visualized and interpreted. In addition, the orthomosaics were predicted using the sliding window prediction.

6.5 Sliding window prediction

To make predictions for full orthomosaics, a grid with a side length of 20 meters was designed. To make predictions for certain tiles, the grid and a sliding window were utilized. A complete orthomosaic was then integrated using these predictions together. This made it possible to predict both training and testing orthomosaics.

6.6 Software and Hardware Environment

The operating system used was Ubuntu 18.04.5, and the hardware configurations consisted of an Intel Xeon 5218R with 64 GB of RAM, an NVIDIA Quadro RTX 5000 with 16 GB of VRAM, and CUDA driver version 11.4 and R version 4.0.4. For the implementation, the DL frameworks Keras 2.3.0 and TensorFlow GPU 2.8 were used.

IV. RESULTS AND DISCUSSION

In the sections below, the results and discussion of the training and classification of the test data set are presented and evaluated.

1 Preliminary Experiments

In the preliminary experiments there were two results to predict the dead spruce trees. which were F1CrossEntropyLoss and the BCE, it is shown in the Figure 19 and 20. From these two, the result with BCE loss model was selected for this research. According to Chicco and Jurman (2020) an F1Score of less than 0.50 is considered as bad performance. Therefore, F1CrossEntropyLoss model can be ignored and BCE results was considered in further testing and predictions. In BCE, there was a minute difference between the loss curves for training and validation. Also, the training accuracy was 0.77. Even though the validation accuracy remains the same.

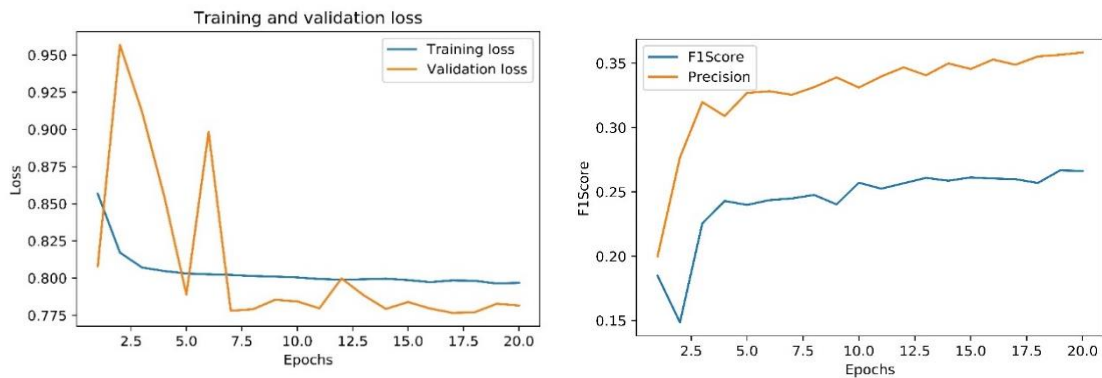


Figure 19: F1CrossEntropyLoss results

2 Training

The training time with BCE per epoch was 2 min 31 s for the training dataset, and it took almost 24 minutes to complete 20 epochs. The training and validation loss curves are plotted in Figure 20.

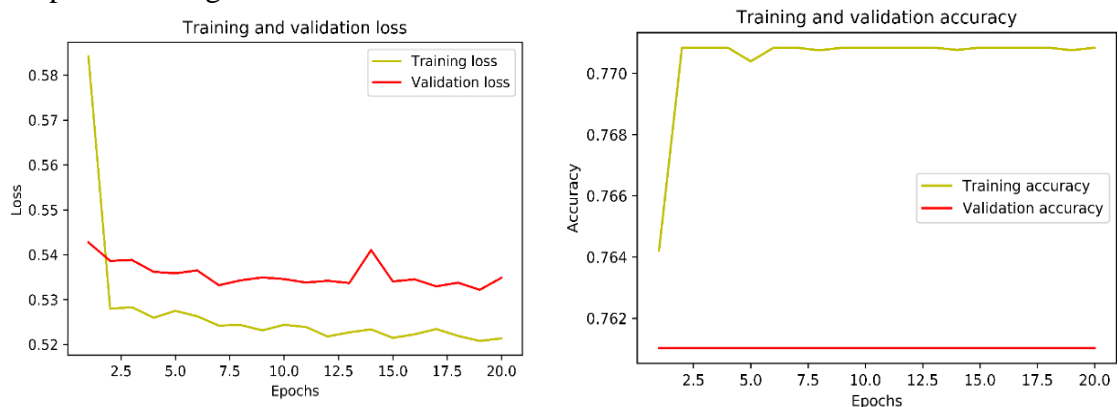


Figure 20: BCE results

Results were visually interpreted to demonstrate that, regardless of the dataset used, the trained network were capable of detecting minute regions of the dead tree canopy. The minute regions of the crowns were not previously labelled because they were smaller than the area being used to label the dead trees. In this context, the presence of leafless crowns of other trees in the winter season could also pose a challenge for image classification, as shown in the prediction of the winter orthomosaic in Figures 24. Therefore, samples from other areas with dead trees should be included as they become available in future work.

2.1 Evaluation

After the training process completed, the trained model was used to classify some of the test data sets, predicted test data set as shown in the Figure 21.

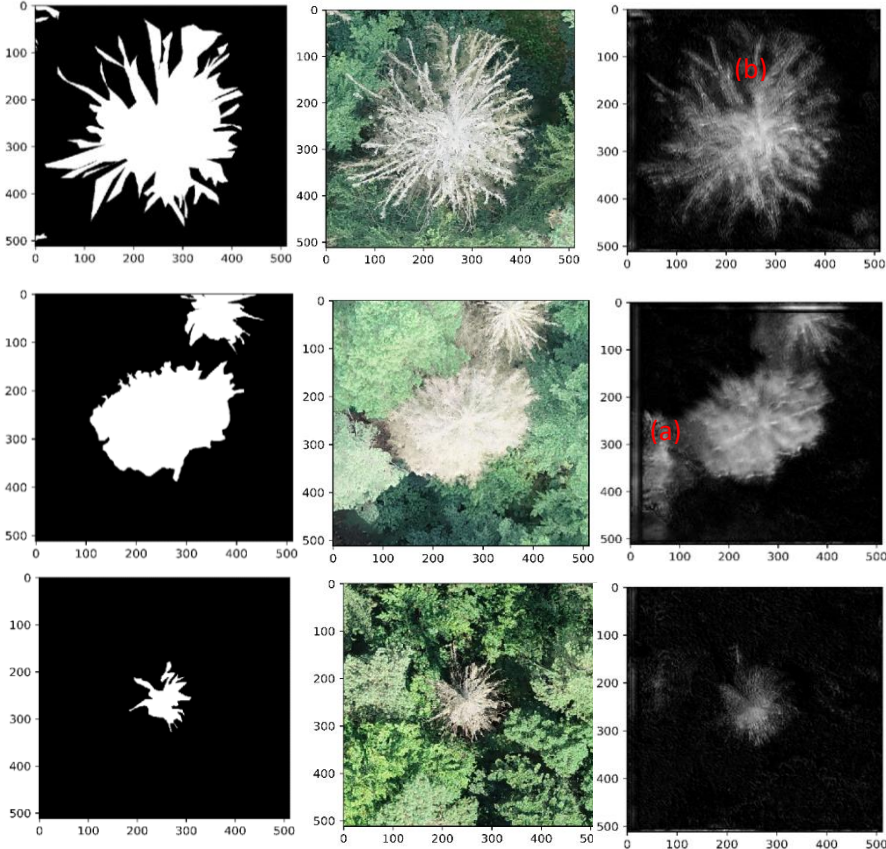


Figure 21: Predicted samples of the test data set; left: Tree mask; centre: test samples; right: Predicted result. In some parts of the image, yellow leaves and the ground were detected as pixels of dead trees (a). Smaller parts of the tree tops that were not masked because they were difficult to label were also detected (b). Both effects resulted in lower accuracy.

2.2 Prediction

The trained model was used to obtain predictions for the entire orthomosaics. Figure 22-23 shows an area of the same site used for model training. To make the prediction of the orthomosaics, the model was fed individually cropped images that were selected with a grid as described in Section 6.5. The images output from the model were then combined into a mosaic to produce the fully predicted mosaic.

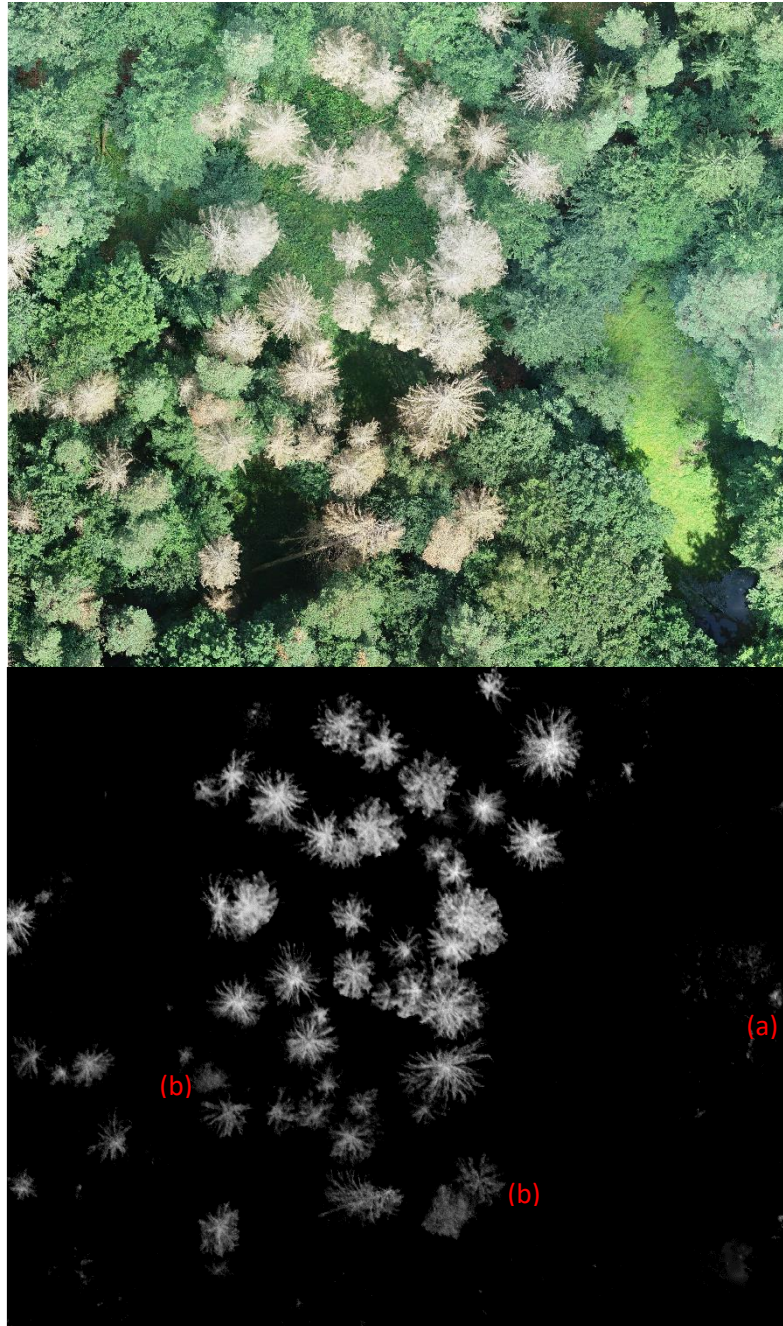


Figure 22: Prediction and orthomosaic of the training dataset. Wrong predictions (a) Predictions with low accuracy (b)

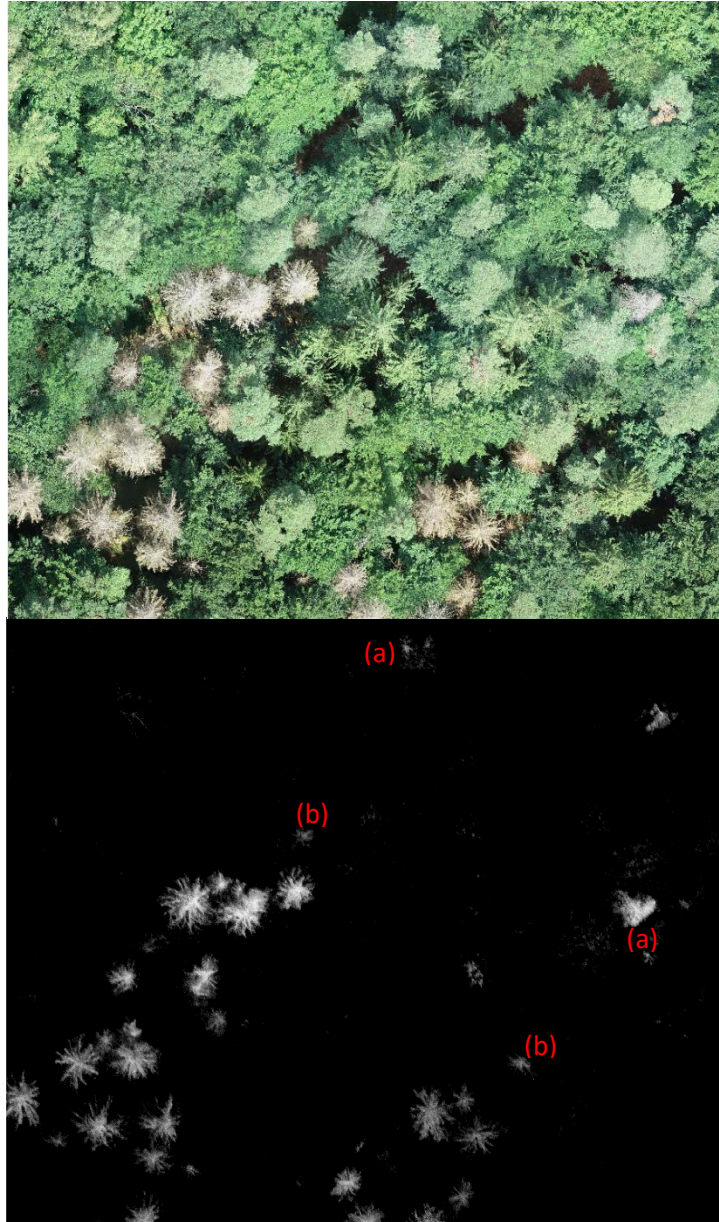


Figure 23: Prediction and orthomosaic of the training dataset. Wrong predictions (a) Predictions with low accuracy (b)

The labelled 147 dead spruce trees were detected in the entire orthomosaic prediction results shown in Figure 25, although 15 detected trees were not clearly segmented. In addition, a few other dead tree species were predicted.

3 Testing

The second objective of the thesis was to use the model for predicting a UAV-orthophoto with different resolution to verify the performance of the model. The UAV images were predicted using sliding window prediction, and the results are shown in Figures 25 - 26. In these predictions, it was clear that the model predicted the dead tree pixels with their

shapes, although it is not accurate because the model was trained with different resolutions of the dataset. In this test UAV orthophoto, the predictions seem to be difficult to quantify the number of dead trees because of the prediction accuracy.



Figure 24: Prediction and orthomosaic of the testing dataset

V. CONCLUSION

This research was started with a comprehensive concept of forest management. There are many problems that forests face nowadays, such as bark beetle infestation, water shortage, etc. One of the main problems that affect the health of the forest is dead trees near healthy trees, which can then fall down or be attacked by insects. These problems greatly affect the health of forests, which is obviously a reason for climate change and global warming. Therefore, a proper management strategy should be in place to quantify the number of dead trees. There are a number of methods to segment the dead trees.

Currently, there are a number of technologies that can be applied to classify dead trees. In this technology-based approach, a combination of RS data and AI can bring a better solution. In this study, RS UAV data and DL model U-Net were used to perform semantic segmentation of UAV orthophotos to classify dead spruce trees. The results reveal that the semantic image segmentation using U-net architecture and the combination of a suitable training method for dead spruce tree detection on UAV orthophotos are effective. The network was trained using several experiments as preliminary tests by altering the pixel size, the number of parameters, etc. As a result, the U-net was trained using BCE as the loss function, 512×512 pixels, and accuracy as the metric. However, the model (BCE) used for prediction showed a slight overfitting, which can be resolved by using more training data sets and adjusting the U-net architecture. Even though a very good visual explanation of the classification results was achieved by using the BCE model with the available data.

Future Work

Additional modifications are necessary to achieve the suggested model's full classification performance. Residual layers are intended to improve training effectiveness due to the computational expenses associated with higher input layer precision (Romera et al. 2018). A self-calibrated convolution is also being investigated for implementation. The proposed architecture is included in the mask prediction branch of a mask R-CNN with the end goal of instance segmentation of the dead and subsequent quantification of the number of trees detected (Thompson et al. 2020).

Another point to consider is creation of an artificial training dataset with numerous canopies based on an augmentation technique where dead trees are randomly replaced to different backgrounds. In order to improve generalization capacity without encouraging overfitting, it is also being examined whether random deletion may be used in conjunction with augmentation (O'Gara and McGuinness 2019). Generative Adversarial Networks (GANs) are a very promising method for training a model with synthetic images, which can also be utilized (Frid-Adar et al. 2018). In addition, the training dataset can be used at different resolutions. Additionally, as the environment changes with the seasons, such as in the ground vegetation and the fallen tree leaves, efforts are required to include training samples from several seasons in the training dataset

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VII. APPENDICES

1. Repository Link

https://github.com/muhammedsinan1997/Semantic_Segmentation_of_dead_trees .This is the link to the repository to get the codes used in this master thesis.

2. Prediction results of whole orthomosaics

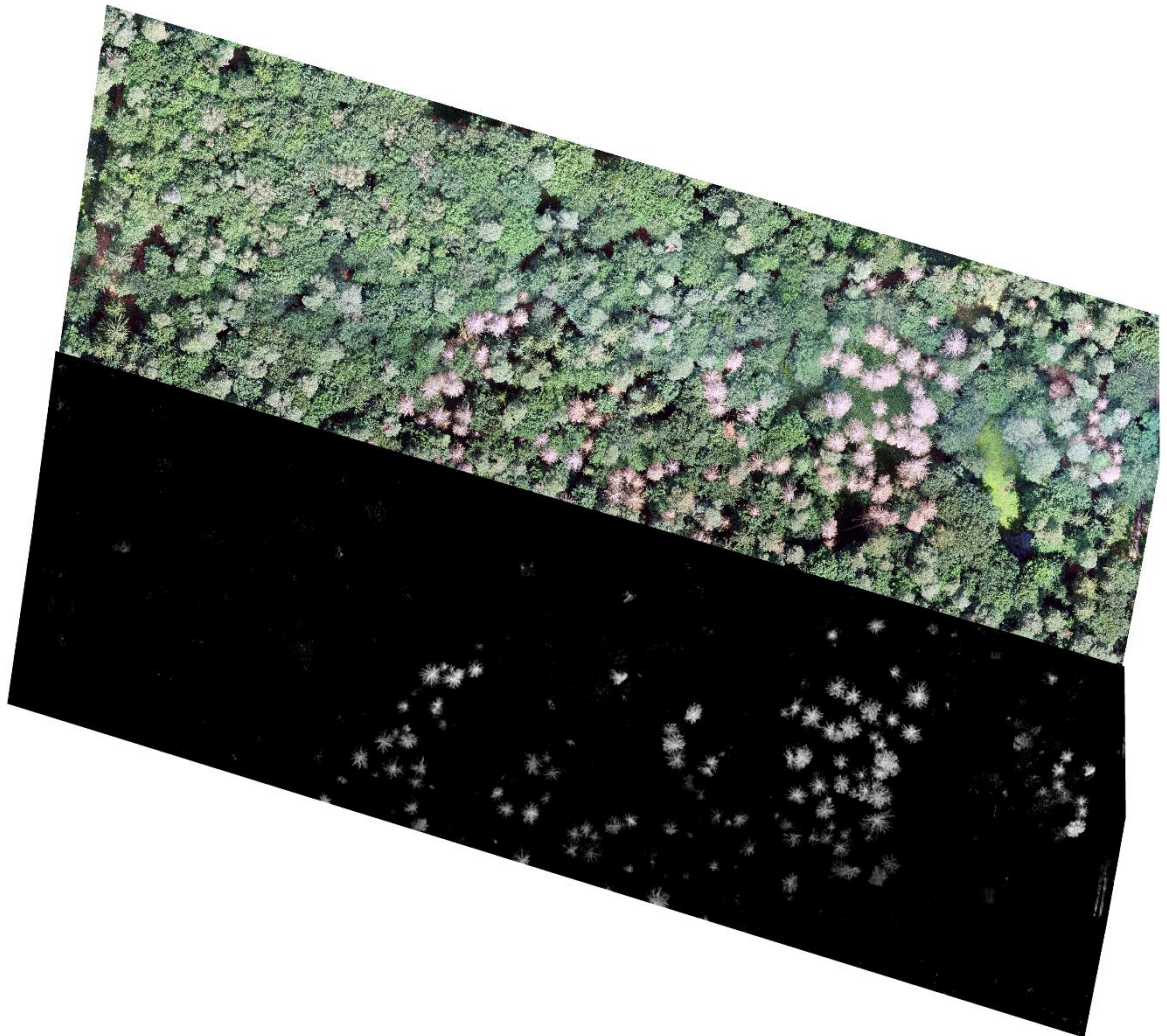


Figure 25: Complete Prediction and orthomosaic of the training dataset

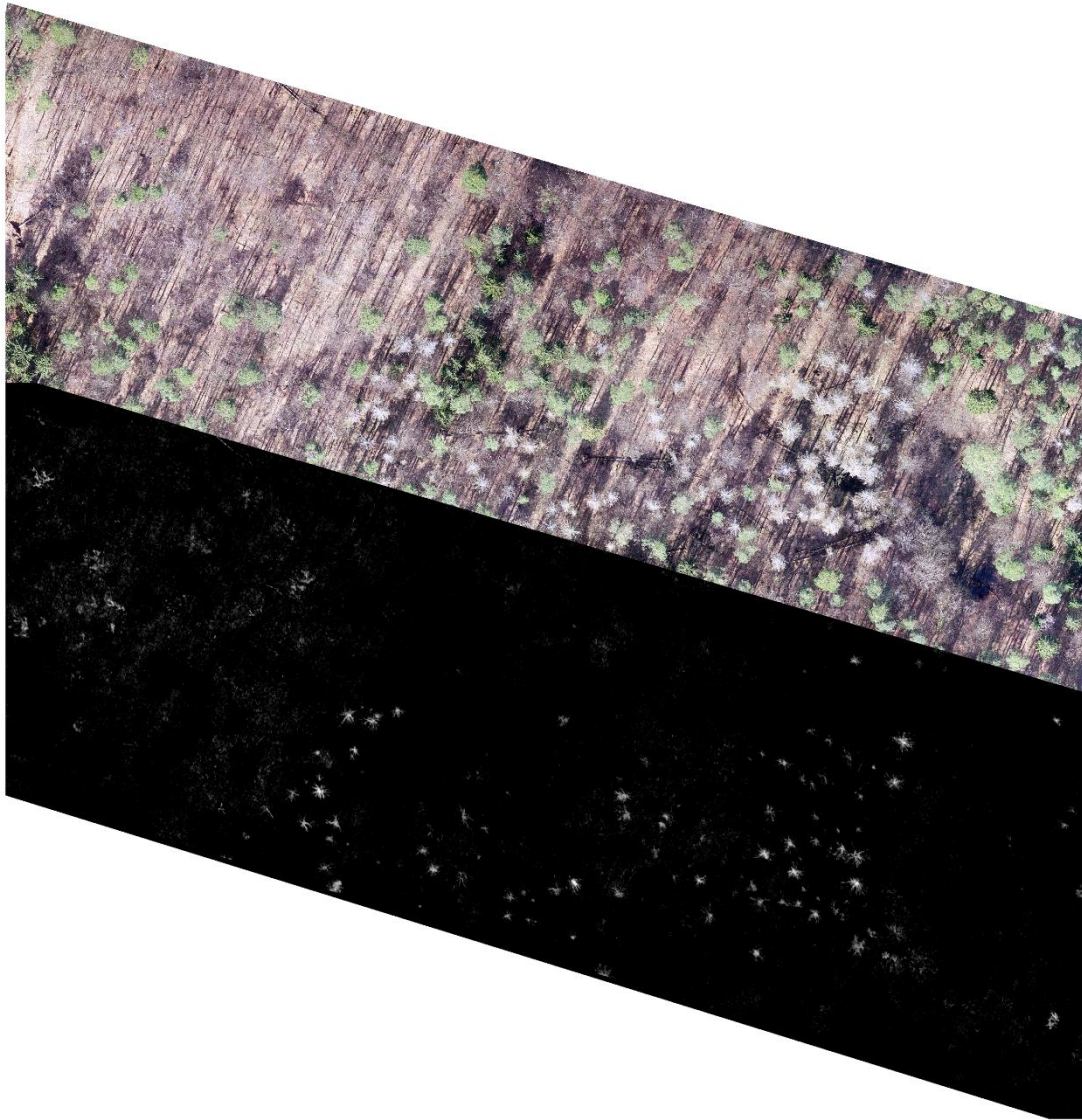


Figure 26: Complete Prediction and orthomosaic of the testing dataset

3. Photographs from the data collection



Figure 27: Ground data collection



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List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
UAV	Unmanned Aerial Vehicle
CNN	Convolutional Neural Networks
ANN	Artificial Neural Network
FCN	Fully Convolutional Networks
BCE	Binary Cross Entropy
RS	Remote Sensing
ESA	European Space Agency
DSM	Digital Surface Model
DTM	Digital Terrain Model
CHM	Crown Height Model
IoU	Intersection Over Union

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