Two-Dimensional Convolutional Neural Networks for Wood Quality Assessment

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ABSTRACT

Different materials, including wood, have been tested using the contact Ultrasonic Testing (UT) technique. The time and velocity of the ultrasonic wave in a wood section have traditionally been monitored and correlated with wood quality. This practice, however, has not yielded satisfactory results, prompting researchers to develop new strategies to address the issue. In this study, the primary objective is to employ convolutional neural networks (CNN) to assess wood quality using the results of contact ultrasonic testing. To this end, 2D CNN models are employed to train on labeled ultrasonic signals as the training set. The developed models are thus set to solve supervised classification problems based on data gathered from testing specimens with various health conditions. The tested specimens are two types of wood with and without natural imperfections. Therefore, the size and shape of damage are different across specimens-billets harvested from trees at two sites in NSW and WA, Australia. This study aims to visualize and investigate the properties of the features extracted by the inner layers of the developed CNN models. This way, an unsupervised strategy can be devised to solve the clustering problem of woods based on their health condition.

INTRODUCTION

Various steps involved in modern Fault Detection and Diagnosis (FDD) systems include (1) representing the knowledge embedded in a system, (2) adapting tools to acquire and process data, (3) classifying systems based on their health status, and (4) making decisions regarding maintenance [1]. Wood products are one of the systems traditionally monitored for decay through visual inspection. In this way, any external evidence of decay in a tree was sought. The most evident sign of this type of decay includes wounds on the trunk of a tree caused by the self-pruning process. Therefore, novel non-destructive techniques can greatly benefit the mechanized harvesting industry, as knot clusters on a

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tree trunk can compromise the quality of wood products [2].

The mechanized harvesting industry relies heavily on wood quality assessment [3]. The presence of clusters of knots on a tree trunk can compromise the quality of wood products [2]. Therefore, novel non-destructive techniques can be of great advantage to this industry.

Ultrasonic tomography has been demonstrated effective for monitoring the quality of standing trees [4]. Several features from ultrasonic testing results, including the wave velocity and time of flight, correlate with the geometry of the defect in the wood section. It was also discovered that any defect could attenuate the ultrasonic wave velocity and increase damping [5]. More advanced techniques exploit signal processing to derive more descriptive features that can characterize defects in wood sections. For instance, Mousavi et al. utilized the Empirical Mode Decomposition (EMD) algorithm to decompose an ultrasonic wave into its constituent modes. They demonstrated that the maximum eigenvalue of the constructed covariance matrix, obtained from the decomposition results, can be used to characterize imperfections in the wood, particularly hardwoods [6].

Machine learning algorithms have been widely used to classify Ultrasonic test results. Krajnc et al. developed binary logistic regression on ultrasound velocity and damping to predict the internal quality of stating trees [5]. Mousavi et al. developed a more advanced time-frequency feature extraction algorithm using the Variational Mode Decomposition (VMD) to be further used to classify wooden sections based on their health state using various machine learning models [7, 8]. Fathi et al. developed a machine-learning model to predict the modulus of elasticity (MOE) and rupture (MOR) of wood with varying moisture content (MC) using the guided Lamb wave technique [9]. Nasir et al. constructed decision tree models to identify the MOE and MOR of UV-degraded wooden samples [10].

The present work demonstrates employing a two-dimensional CNN network for feature extraction and solving the classification of woods based on their health state. This way, the contact–ultrasonic technique is demonstrated to be useful for identifying healthy standing trees. To this end, two types of billets harvested from trees at different sites in two Australian states, i.e., WA and NSW, are studied.

PROBLEM STATEMENT

The problem of standing tree classification based on their health status, originally presented in [11], is investigated in this paper. Several billets harvested from trees in two Australian states, i.e., New South Wales (NSW) and Western Australia (WA), were selected for investigation. Several types of Eucalyptus species were studied, including Eucalyptus Pilularis (Blackbutt), Eucalyptus Marginata (Jarrah), and Eucalyptus Punctata (Grey gum). An ultrasound device, i.e., Pundit PL-200 [11], was employed to test the billets in several randomly selected directions. The billets were visually inspected and classified as either "intact" or "defective." Subsequently, the ultrasound data was fed into a two-dimensional (2D) Convolutional Neural Network (CNN) to address a classification problem within a 5-fold classification scheme.

Table I provides specific details about the tested types of wood and the corresponding en-

TABLE I: TYPE OF STUDIED WOOD AT DIFFERENT SITES AND THE METEOROLOGICAL CONDITIONS UPON TESTING [11].

Species	**State**	**Site**	**Temperature (°C)**	**Humidity (%)**
Jarrah	WA	Collie	5.1	90
Blackbutt & Greygum	NSW	Coffs Harbour	10	90

TABLE II: THE SPECIFICATIONS OF THE TEST SET-UP USING PUNDIT PL200 ULTRASONIC TESTING DEVICE. TF: TRANSMITTED FREQUENCY; PRF: PULSE REPETITION FREQUENCY; SF: SAMPLING FREQUENCY; CG: COUPLANT GEL.

TF	54 kHz
PRF	5 Hz
SF	10 MHz
CG	Proceq Ultraschall-Koppelpaste

vironmental conditions at the testing sites. Table II outlines the specifications of the testing procedure. A transducer operating at 54 kHz was employed to emit a sinc-like probing P-wave (compression wave) with a pulse repetition frequency (PRF) of 5 Hz. The receiver captured the transmitted and modulated ultrasonic waves due to their interaction with irregularities within the wood at a sampling frequency of 10 MHz.

Table III presents the number of ultrasonic tests for billets harvested at different sites.

TWO-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK

The architecture of the constructed 2D CNN is depicted in Figure 1. The deep learning model has several layers, as outlined below:

- The input layer: This layer defines the input image size to be fed into the 2D network. The input image size is 110×72 pixels with a single channel. To obtain this, the Ultrasound signals are reshaped into matrices of the shape 110×72.
- Convolution layer: This is a convolutional layer with 3×3 filters with "same" padding. This means that the output feature map will be the same size as the input.
- ReLU1 layer: The next layer is a rectified linear unit (ReLU)–an activation layer that introduces nonlinearity to the output of the convolutional layer.
- Max-pooling layer: This layer performs max-pooling with a 3×3 window and a stride of 1.
- ReLU2 layer: Another ReLU activation layer.
- Fully-connected layer: This fully connected-layer has two neurons. This layer takes the output from the previous layer and applies a linear transformation to generate a 2-dimensional output.
- Softmax layer: This layer applies the softmax activation function to normalize the output values to a probability distribution.
- Classification layer: This is the final layer of the network and it performs the classification task. It uses the cross-entropy loss function for training the network.

TABLE III: THE TOTAL NUMBER OF ULTRASONIC TESTS CONDUCTED ON BILLETS HARVESTED FROM VARIOUS SITES (SHOWN AS "TESTS @ BILLETS").

Condition	WA	NSW
Intact	838 @ 37	213 @ 7
Defective	897 @ 37	617 @ 28

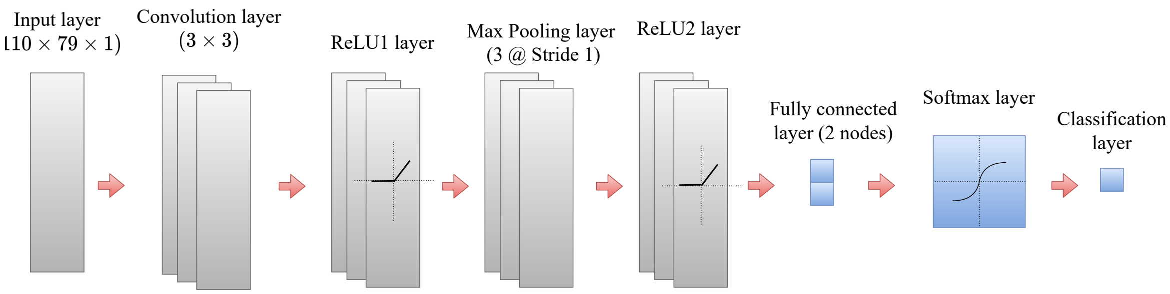


Figure 1. The architecture of the constructed 2D CNN.

The network is trained using stochastic gradient descent with momentum (SGD optimizer)–a technique that aids in expediting the convergence of gradient vectors by directing them towards the correct directions [12]. This approach facilitates faster convergence during the training process. The training options encompass a learning rate of 1e-5, which is scheduled to drop by a factor of 0.2 after every 5 epochs. The training process is limited to a maximum of 50 epochs.

RESULT AND DISCUSSIONS

Table IV displays the classification report obtained from 5-fold cross-validation for the training 2D-CNN models on various data sets. The data was divided into five folds, with the model being trained on four different combinations of the folds while testing on the remaining fold. Further, the Precision, Recall, and F1 scores obtained across different folds were averaged, and the mean and standard deviation of the results are presented as $\mu \pm \sigma$, where μ and σ represent respectively the mean and standard deviation of the reported metrics across different folds. The obtained results for each case are discussed in this section.

Based on the classification results obtained from the 2D-CNN models trained on different folds of the WA billets, the following conclusions can be drawn: The proposed 2D-CNN architecture shows consistent performance across the different folds. This is reflected by the relatively small standard deviations obtained for the accuracy, precision, recall, and F1 scores evaluated across various folds. The model achieves high precision scores for training and test sets with an average value of about 95% and a small standard deviation of less than 1% across different folds. This suggests that the model has a low false positive rate and effectively identifies positive instances. The consistent results obtained from the training and test sets also demonstrate the model's generalizability. The model also demonstrates high average recall scores of 96.6% and 95.6% for the training and test sets, respectively. Although a slightly bigger standard deviation of 3.3% occurs for the test set across different folds–compared to the standard deviation of 1.6% for the training sets–the results are within an acceptable range. This indicates that the model has

TABLE IV: THE 5-FOLD CROSS-VALIDATION CLASSIFICATION REPORT OF THE TRAINED 2D-CNN MODELS FOR VARIOUS TRAINING AND TEST SETS.

	Train			
	Accuracy (%)	**Precision**	**Recall**	**F1**
WA	95.48±1.77	95.2±0.9	96.6±1.6	95.8±0.7
NSW	99.61±0.19	100±0	99.8±0.4	100±0
Mixed	91.07±1.59	91.2 ± 1.3	93.2 ± 1.7	92.2 ± 0.6
	Test			
	Accuracy (%)	**Precision**	**Recall**	**F1**
WA	94.81±2.12	95.0±0.8	95.6±3.3	95.8±1.1
NSW	99.64±0.24	99.8±0.4	99.8±0.4	100±0
Mixed	90.64± 1.64	90.8 ± 1.8	93.0 ± 1.9	92.2 ± 1.0

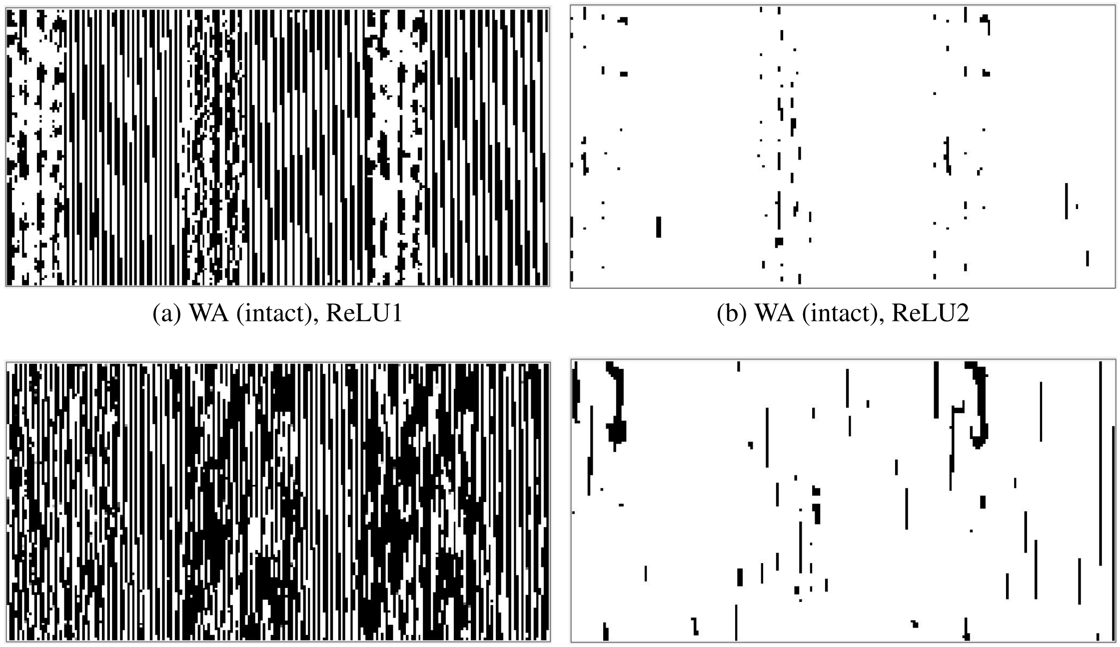
a low false negative rate and can effectively capture many positive instances. The F1 score–the harmonic mean of the precision and recall–has also shown consistent values across the training and test sets with a high average value of 95.8% for both cases. This is while the standard deviation is as small as 0.7% for training and 1.1% for the test. These scores indicate a good balance between precision and recall, reflecting the model's ability to achieve high accuracy while capturing a significant portion of relevant instances. Overall, these results suggest that the CNN model performs well, indicating its capability to classify instances in both the training and test sets accurately. The consistent performance across the folds further strengthens the reliability and generalizability of the model.

The results of the 2D-CNN models trained and tested on NSW samples indicate that the CNN model performs exceptionally well. The precision, recall, and F1 scores are consistently high across all folds, with minimal variation. The model achieves perfect or near-perfect performance, with precision, recall, and F1 scores of almost 100%. The small standard deviations suggest the model's performance is stable and reliable. These results indicate that the CNN model is highly accurate in classifying instances, achieving perfect or almost perfect performance on both the train and test sets.

The findings from the combined analysis of mixed samples demonstrate lower levels of accuracy in comparison to the individual classification of NSW and WA samples. This observation suggests combining samples increases the complexity of distinguishing between intact and defective specimens, resulting in classification confusion.

Intermediate features visualization

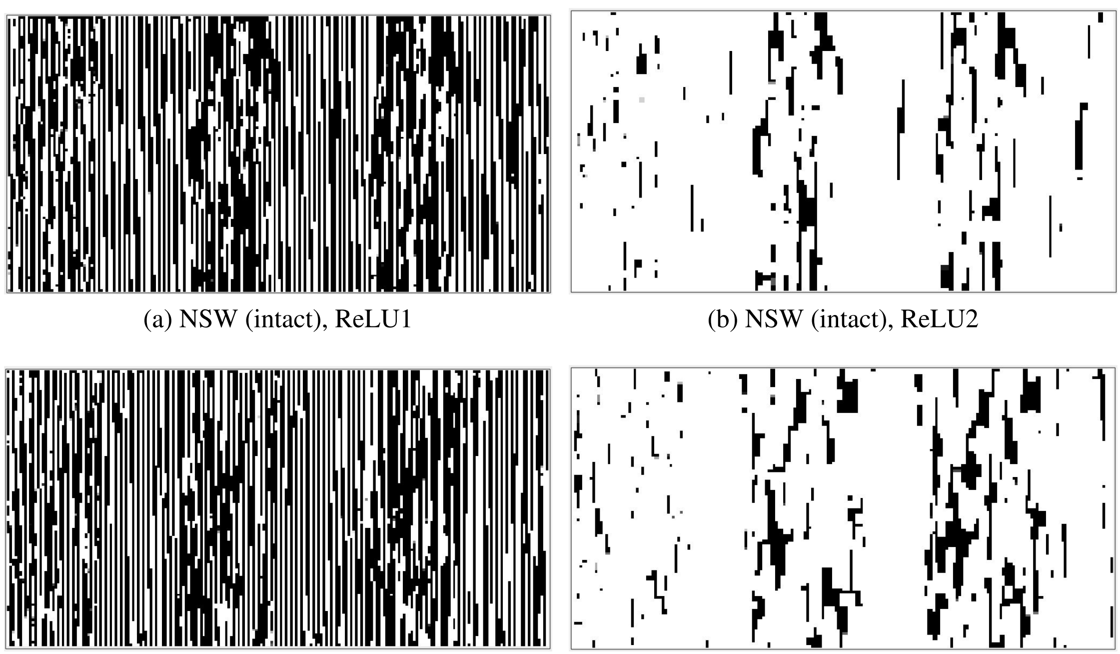
In this section, we visualize the features extracted from the ReLU layers of various models trained on 80% of the WA, NSW, and mixed samples. Subsequently, we employ the models trained on the WA and NSW samples to visualize the learned features from an example of WA and NSW signals, respectively (Figures 2 and 3). Furthermore, we utilize the same examples to visualize the features learned from the model trained on the mixed samples (Figure **??**). These results confirm that the model can acquire distinct features when the samples are combined. The insights gained from this section can serve as a foundation for future research aiming to develop a fully unsupervised classification algorithm.



(a) WA (intact), ReLU1 (b) WA (intact), ReLU2

(c) WA (defective), ReLU1 (d) WA (defective), ReLU2

Figure 2. Visualization of features learned in ReLU layers for an example of WA signal.



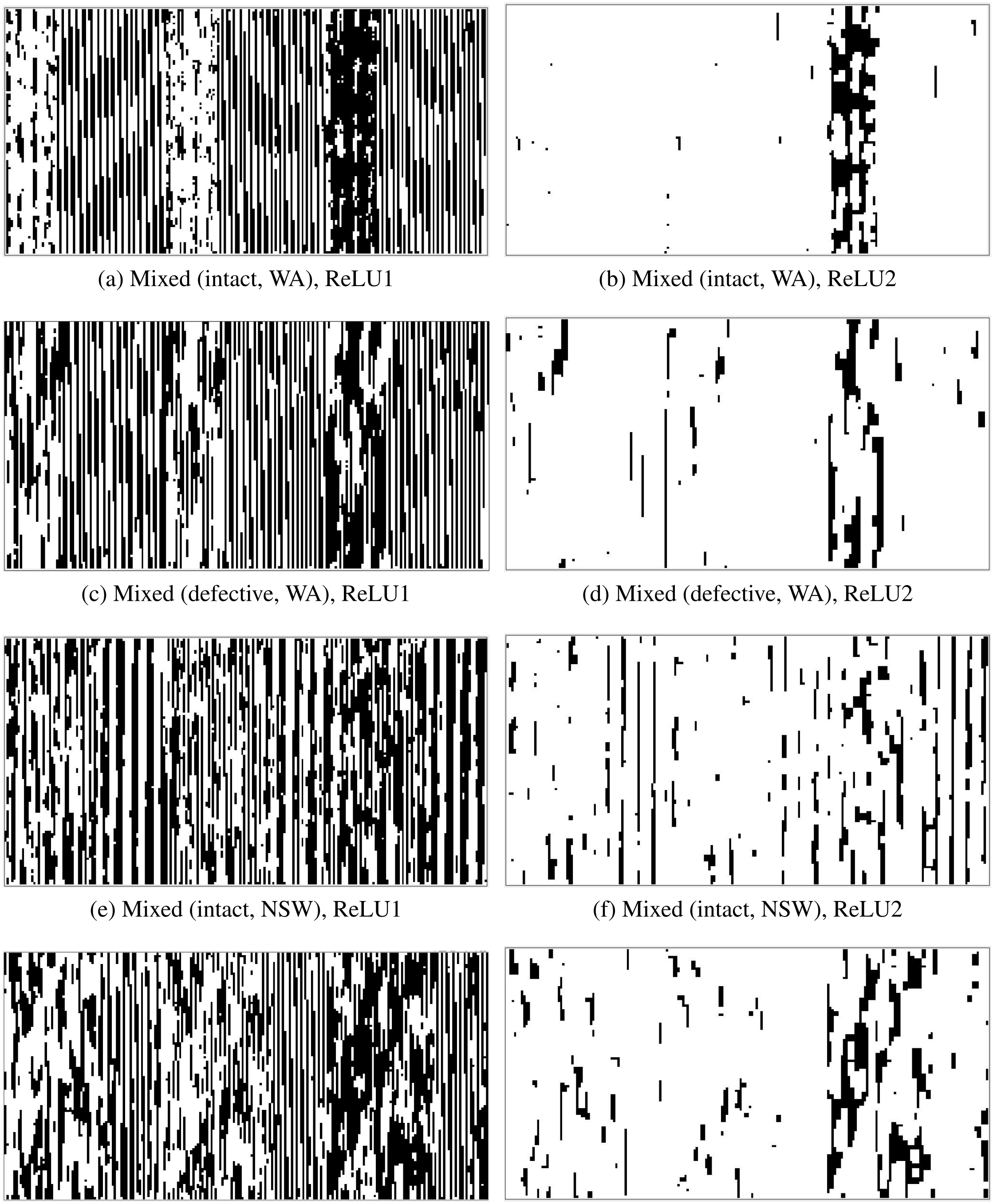
(a) NSW (intact), ReLU1 (b) NSW (intact), ReLU2

(c) NSW (defective), ReLU1 (d) NSW (defective), ReLU2

Figure 3. Visualization of features learned in ReLU layers for an example of NSW signal.

CONCLUDING REMARKS

This paper presents a 2D-CNN architecture designed to address the classification problem of wood samples with internal imperfections obtained from two sites in NSW and WA, Australia. The results highlight the models' exceptional performance in accurately classifying the wood



(a) Mixed (intact, WA), ReLU1

(b) Mixed (intact, WA), ReLU2

(c) Mixed (defective, WA), ReLU1

(d) Mixed (defective, WA), ReLU2

(e) Mixed (intact, NSW), ReLU1

(f) Mixed (intact, NSW), ReLU2

(g) Mixed (defective, NSW), ReLU1

(h) Mixed (defective, NSW), ReLU2

Figure 4. Visualization of features learned in ReLU layers for an example of NSW and WA samples using a model trained on mixed samples.

samples harvested from the WA or NSW as intact or defective individually. However, once the signals are combined, difficulties in sample classification arise. Visualizing features learned from the ReLU layers in the models reveals that mixing the samples led to acquiring entirely distinct features. As a result, future work will focus on enhancing either the architectural model or pre-processing the signals in order to: 1) achieve a higher classification accuracy in mixed samples and 2) employ the acquired sample representations from supervised models to tackle unsupervised classification of wood samples based on their quality.

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