International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 2, April 2023, pp. 2156~2166
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i2.pp2156-2166

A review of the automated timber defect identification approach

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Article Info

Article history:

Received Feb 14, 2022
Revised Sep 27, 2022
Accepted Oct 30, 2022

Keywords:

Automated vision inspection
Timber defect identification
Deep learning
Convolutional neural network
Machine learning

ABSTRACT

Timber quality control is undoubtedly a very laborious process in the secondary wood industry. Manual inspections by operators are prone to human error, thereby resulting in poor timber quality inspections and low production volumes. The automation of this process using an automated vision inspection (AVI) system integrated with artificial intelligence appears to be the most plausible approach due to its ease of use and minimal operating costs. This paper provides an overview of previous works on the automated inspection of timber surface defects as well as various machine learning and deep learning approaches that have been implemented for the identification of timber defects. Contemporary algorithms and techniques used in both machine learning and deep learning are discussed and outlined in this review paper. Furthermore, the paper also highlighted the possible limitation of employing both approaches in the identification of the timber defect along with several future directions that may be further explored.

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1. INTRODUCTION

The term 'timber' has several connotations and is used synonymously with the term 'lumber' in many regions of the world. Timber most often refers to diverse species of wood of various sizes and categories, which enable it to be used widely as a fuel source, construction material, furniture, timber beams, and various other applications. Before the debut of automated vision inspection (AVI) in the wood industry, a conventional method involving human operators physically inspecting timber to identify and categorize defects was widely used in primary and secondary wood industries. Unlike AVI, manual inspections do not require a technical setup and they tend to provide less value for future development due to constant changes to standard operating procedures with regard to the discovered defects. However, due to uncontrolled deforestation, which has led to a decline in forest resources and a spike in timber costs, the majority of wood sector operators have decided to employ AVI to optimize resources and reduce production costs, while maintaining product quality. Besides, timber costs account for almost 70% of the overall production cost in the secondary wood industry compared to other costs, especially in the production of timber, followed by the constant rise in labor costs, which is aggravating the situation [1]. Nevertheless, wood industries need to find a solution to enhance timber processing so as to boost the yield of timber while maintaining the quality of wood products. Unlike other sectors that employ AVI, wood industries often delegate the task of examining timber to human operators, where such manual inspections can lead to human error, depending on the experience of the workers, the level of their skills, and their alertness [2]. Three-quarters of the judgement of the human operators were inaccurate, resulting in an absolute yield loss of nearly 16.1% from the overall yield [3]. A related study on the ability of furniture rough mill workers to spot wood defects also showed that the precision of the human operators was capped at an average of 68%. A high production volume and repeated activities over a prolonged period of time will affect human operators, who are likely to become exhausted, depressed, and overwhelmed, resulting in low accuracy and poor quality of inspection [4]. In addition, one cause of concern is the number of well-trained inspectors in the current market environment, which continues to stagnate or decline gradually in contrast to the constant growth of the industry [5].

The use of AVI is often emphasized to ensure the constant reliability of a product, while resolving current challenges that have resulted in yield losses due to inadequate inspections performed by human operators. Research found that compared to the traditional method of inspection, the AVI would be able to boost the accuracy of detection by 25%, thereby resulting in an increase of 5.3% in yield, which would mean cost savings for the average rough mill [6]. Automated timber grading has been proven to be more accurate and reliable than the conventional inspection approaches, which are claimed to be ineffective in improving timber resources [7]. In general, several studies have shown that AVI is more effective in identifying timber defects than human operators and is more reliable in the process of quality control, hence benefitting the secondary wood industry by increasing timber yields and production quality [8].

2. METHOD

The detection and identification of defects are crucial in the manufacturing industry to ensure that a manufacturing process is under control and running smoothly [9]. Furthermore, human operators with prior experience in the field presently carry out these processes manually, and the implementation of the AVI is able to improve the autonomy of the manufacturing operation. Quality control with the assistance of the AVI is gaining more traction in the manufacturing industry, particularly in the secondary wood industry, due to its ability to improve the inspection process and the rate of production, while lowering labor costs for the manufacturer. The AVI is comprised of several segments known as image acquisition, image enhancement, segmentation, feature extraction and feature classification [10], while material handling is part of the hardware components of AVI that is used for material logistics, where the proper handling of materials is crucial for a steady material movement, vibration mitigation, and maintaining the correct speed throughout the acquisition of timber images. In addition, several subsystems such as sensors and lightings are involved in the processing, digitalization, and storage of image data. In general, the defect detection components are the first aspect of the inspection process, which involves determining the location of the timber defect. The discovered defect will then be processed by the defect identification components to determine the type of the defect, as well as its size and frequency. Furthermore, the defect identification and detection components serve as a guideline for the optimized cutting of the timber according to the discovered defect. This data will subsequently be used as the input for the timber grading component, which will grade the timber according to the rules defined by the production requirements.

Despite the fact that AVI has been adopted in the wood industry since 1983, there are still ongoing research efforts to improve the inspection process in areas such as defect detection and identification, defect characterization, wood grading and integration of sensors into hardware components for the purpose of optimized cutting. With the arrival of Industry 4.0, there has been an increasing demand among industry players, particularly in manufacturing, for the defect identification process to be automated [11]. Hence, research into the development of low-cost systems using artificial intelligence and internet of things (IoT) technologies is the best approach to accommodate the needs of manufacturers. In the wood industry, any abnormality on timber surfaces that may reduce its strength, durability or appearance is considered as a defect. 'Natural' defects occur during the growth of the trees, while 'mechanical' defects occur due to poor conversion, seasoning or handling during the processing and manufacturing of the timber. Aberrations with regard to the texture, color, and shape of the timber are the typical characteristics that are examined during a visual surface inspection for the identification of wood defects in the secondary wood industry. Besides, additional grading rules are in place to segregate timber into permissible and non-permissible groups based on the severity of the defects. Regardless of the timber species, both mechanical and natural defects are likely to occur. Although there are different forms of defects in timber, the texture, color, and shape of these defects are generally identical across all timber species. The existence of such defects will definitely have an impact on the quality and strength of the timber across all species. Hence, it is important for those defects to be detected and identified throughout the various stages of timber processing such as grading, cutting, and sorting. Table 1 lists the various types of defects categorized by previous works into the AVI. It is clear from this table that most research worked on knots rather than on other types of defects. This is due to the fact that knots are a type of defect that is most frequently found in timber. Knots also affect the structural strength of the timber, and hence, the overall quality of the final product. It is notable that most researchers either worked on one type of defect or only a few types (less than 5). This indicates that there is a gap between working to generalize and characterize all the types of defects that are frequently found.

Table 1. Previous AVI works categorized by defect types

Defect Type	Reference
Knot	[5], [12]–[28]
Crack	[14]–[19], [21], [22], [25]
Hole	[13], [14], [19], [20], [23], [24]
Pocket	[5], [13], [17], [29]
Stain	[13], [25], [30]
Decay / Rot	[20], [24]
Split	[5], [13], [20]
Wane	[5], [13], [20]

Generally, there are two types of research problems when dealing with AVI in the wood industry, namely, defect detection and defect identification. Table 2 lists the previous AVI studies related to the detection and identification of timber defects. The difference between these two approaches depends on their final output, where the detection approach focuses on the process of locating wood defects based on a computer vision technique such as segmentation [31]. In working on the problem of detection, Luo and Sun [18] suggested a local binary threshold segmentation algorithm for the detection of wood image defects by calculating the threshold based on the mean, standard deviation and extreme value of the window. Their research managed to achieve an accuracy of 92.6% for wood defect images with a complex background. In addition, Pahlberg [32] conducted to further investigate the use of vibrothermography for the detection of cracks in parquet lamellae, where an accuracy of 80% was achieved by capturing the texture image using completed local binary pattern histograms and segmenting the cracks with background suppression and thresholding. Likewise, the use of the three-dimensional stress wave imaging method for detecting internal defects in wood on PT-Kriging (particle swarm optimization (PSO) Top-k Kriging) achieved a relative error ranging from 11.57% to 28.74% compared to the use of the TIDW algorithm, which had a relative error (%) between 8.69 and 46.28 [33].

In another work, Hashim *et al.* [34] achieved an average wood defect detection accuracy of 81% across four types of timber species and eight different types of wood defects by using the Mahalanobis one-class classifier (MC) with a fast minimum covariance determinant estimator (MC-FMCD) in their timber defect detection research. On the other hand, wood defect identification emphasizes on classifying wood defects using statistical classifier techniques such as machine learning and deep learning [35]. Ding *et al.* [36] proposed an improved solid-state drive (SSD) algorithm, which includes a single-shot multi-box detector SSD, a target detection algorithm, and a DenseNet network, for identifying defects in solid wood panels. As a result, the accuracy and checking by the algorithm with regard to active knots and dead knots increased to 96.1% in comparison to the previous version. Alternatively, researchers have developed an identification algorithm using local binary pattern (LBP) and a local binary differential excitation pattern on birch veneer that incorporates crack and mineral line defects [37]. The research has shown that the proposed algorithm can better identify cracks and mineral lines with recall (0.930), precision (0.943), and false negative rates (FNR) (0.070). Chang *et al.* [19] found that the final identification rate of cracks and pinholes can reach 96.3% by utilizing the classification and regression tree method (CART). It was emphasized by Sandak *et al.* [38] that both methods of wood defect identification based on the partial least square discriminant analysis (PLS-DA) and non-linear support vector machines (SVM) classification are capable of effectively classifying defects with an average accuracy of 95%. Guoxiong *et al.* [39] further claimed that combining a singular spectrum analysis for signal filtering with SVM for wood defect identification can achieve an identification rate of 95% among knot specimens.

Table 2. Previous AVI studies on defect detection and identification

Defect type	Reference
Defect detection	[20], [24], [30], [40]–[45]
Defect identification	[8], [13]–[15], [21]–[23], [25]–[27], [29], [37], [39], [46]–[50]

3. APPROACHES FOR THE IDENTIFICATION OF TIMBER DEFECTS

In wood industries, one of the most effective techniques for identifying defects is to process and analyze images of wood surfaces with defects. Several studies have been conducted on AVI employing traditional image processing, specialized processing techniques as well as artificial intelligent techniques [51]. Prior defect identification, traditional image processing techniques such as edge detection and image segmentation are often utilized for the detection of defective patterns that are consistent and distinguishable from the background [52]–[56]. Furthermore, the adoption of blob detection algorithms for defects on tile surfaces [57] and the feature-based histogram technique for the detection of defects in a textured surface [58] are examples of specialized processing techniques for surface defect detection. As there are uncertainties in terms of the intensity of the defects in various shapes and sizes of wood, it is crucial to develop learning-based methods that can adapt to such a wide variation. Due to their robustness with regard to variations in wood defects, learning-based approaches using machine learning and deep learning would be a better option than pre-programmed feature-identification methods. Besides, the identification of wood defects using statistical classifier techniques such as machine learning and deep learning can provide such robustness [35]. These machine learning approaches classify wood defects by factoring the statistical variations of the defect images to learn about the desired defects with the assistance of several classifiers such as neural networks [59], *k*-nearest neighbors (*k*-NN), decision trees and SVM [17]. On the contrary, deep learning has been shown to be highly effective in a wide range of image-based applications, including object detection and identification, facial detection and pattern identification due to their network flexibility in discovering custom defects based on the dataset [60]–[64]. Furthermore, feature extraction for deep learning is embedded in the learning algorithm, where features are extracted in a fully-automated manner, without requiring any intervention from a human expert. The implementation of convolutional neural networks (CNNs) is an example of automated feature extraction using deep learning approaches [22]. Regardless of the learning model, the goal of utilizing machine learning and deep learning for the identification of wood defects is to adapt new data independently, and make decisions and recommendations based on thousands of calculations and analyses with a lower factor of human error.

3.1. Machine learning in the identification of timber defects

In the identification of timber defects using artificial intelligence, machine learning is tasked with developing algorithms that learn from datasets, and improving their accuracy over time without being explicitly programmed to do so. As opposed to other algorithms, machine learning is trained to forecast types of defects based on the explored dataset by leveraging its capability to recognize patterns and features [65]–[67]. Besides, the algorithms are capable of evolving over time as more data is processed, resulting in improved decision-making and prediction accuracy. The machine learning technique is frequently used for identification, estimation, prediction, affinity grouping, clustering, estimation and visualization [68]. Besides, the model also comes with methods, theories, and application domains because of its connection to mathematical optimization. Additionally, the unsupervised learning paradigm can be implemented in machine learning to aid learning and the establishment of baseline behavioral profiles for various entities in order to find significant abnormalities [69]. As suggested by Ongsulee [70], machine learning training is made up of four categories, which are supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. However, supervised learning and unsupervised learning are the machine learning methods that are adopted the most, with supervised learning accounting for 70% of the implementations, followed by unsupervised learning close to 20%. Supervised learning occurs when the algorithms are taught using labelled data, whereas unsupervised learning occurs when the algorithms are trained with an unknown set of classes. The objective of unsupervised learning is to explore the data and find some structure within. Semi-supervised learning, on the other hand, utilizes both labelled data and unlabeled data during the training. However, this sort of learning approach is beneficial when the cost of labelling is too high for a fully-labelled training process. Meanwhile, reinforcement learning requires the algorithm to figure out which actions yield the most rewards through trial and error. The goal of reinforcement learning is to discover the most effective policy. Along with different types of training algorithms, these algorithms can be further separated into two types of classification methods, known as eager learning and lazy learning, based on their data abstraction processes [68]. Eager learning approaches generate a general, explicit description of the target function based on the available training samples, whereas lazy learning approaches simply store the data and wait until an explicit request is made to generalize beyond these samples.

In the wood industry, machine learning was used to classify knots and fractures in oak, spruce, and TMT spruce sawn timber in a study conducted in 2020, where an SVM was able to obtain a defect identification accuracy of 75.8%, followed by accuracies of 74.2% and 71.9% obtained by *k*-NN and decision tree, respectively [25]. In addition, Mohan and Venkatachalapathy [71] also conducted an experiment that combined bagging with a number of classifiers, including the Naive Bayes, random forest, and *k*-NN. The random forest classifier outperformed all the other classifiers in the experiment, with an accuracy of 81% in recognizing wood knots. Next, Hau *et al.* [72] proposed an evaluation of alternative feature extraction and identification of wood defect images by comparing six types of feature extraction approaches with numerous machine learning classifiers such as SVM, decision tree, and random forest. The study was able to achieve the highest correct identification rate of 82% using the SVM classifier and gray-level co-occurrence matrix (GLCM) feature extraction method. Nevertheless, some research that used a particle swarm optimization-based lazy learning particle classifier yielded promising results [33], [73]. However, exceptions were made for two machine learning research that accomplished competitive results by using near-infrared (NIR) sensors instead of ordinary cameras [16], [38]. The research, however, could not be equitably analyzed due to the implementation of different technologies.

Unlike other conventional machine learning classifiers, neural networks have lately piqued the interest of researchers due to their potential to achieve greater accuracy than other standard classifiers. Peng *et al*. [44] proposed a simultaneous wood defect and wood species identification strategy based on 3D scanning and signal processing for back propagation (BP) network training and identification using the neural network toolbox. The findings indicate that their approach can effectively identify defects with a relative error of less than 5% and also recognize wood species with an accuracy of 95%. With a defect identification performance of 65.4% in [13], artificial neural network (ANN) outperformed other standard classifiers including the k-NN and decision tree. By fine-tuning the displacement and quantization parameters of the statistical texture of defect images before they are trained using a neural network model, the wood identification accuracy could be improved to 94% [2]. Ji *et al.* [49] proposed a diversified feature extraction and defect identification approach that included a Hu invariant moment, wavelet moment, and BP neural network, with both feature extraction methods that were paired with the BP neural network achieving an average accuracy of 93.67%. Throughout the study by Thilagavathi and Abiram [29], six classes of wood defect datasets were used to test various neural network training algorithms, including the Levenberg-Marquardt algorithm (*trainlm*), scaled conjugate gradient algorithm (*trainscg*), gradient descent adaptive learning algorithm (*traingda*), Bayesian regularization (*trainbr*), and resilient backpropagation (*trainrp*). The Bayesian regularization and backpropagation training methods outperformed the other competitors with an accuracy of 98.2%. The above discussion on wood defect identification based on various types of classifiers is summarized in Table 3.

Table 3. Related works on various machine learning approaches for wood defect identification

Classification methods	Classifier	Reference
Eager learners	Decision tree	[17], [59], [72]
	Random forest	[32], [72], [74]
	Naïve Bayes	[59], [71], [75], [76]
	SVM	[16], [17], [24], [38], [45], [76]–[78]
	Neural network	[8], [14]–[16], [29], [40], [46], [47], [49], [59], [75]–[77], [79]–[83]
Lazy learner others	k-NN	[17], [27], [59], [72], [78]
	Particle swarm optimization	[17], [27], [59], [72], [78]
	Genetic algorithms	[73]
	Bees algorithms	[84]

3.2. Deep learning in the identification of timber defects

Despite the fact that machine learning can accomplish tasks without being explicitly programmed, the computer still thinks and acts like a machine, and its ability to perform some complicated tasks falls far short of what humans can do. Deep learning, on the other hand, is a subset of machine learning in which the establishment of multi-layered neural networks is modelled after the human brain and uses the same mechanisms to grasp inputs such as images, sounds, and texts [85]. The algorithms within each layer of the deep learning neural network are constantly performing calculations and making predictions in order to improve the accuracy over time. deep learning is also an approach based on the characterization of data learning, where an observed image can be expressed in a variety of ways, for example, as a vector of each pixel density value, or more abstract properties like a series of edges [86]. Ever since the convolutional neural network (CNN) won the ImageNet large scale visual challenge (ILSVRC) competition, image analysis based on deep learning has been widely adopted by researchers due to its ability to outperform other identification methods and obtain high accuracy scores [87]. While the CNN is often employed for image or spectrum identification, a few studies have focused on its use for the identification of timber defects. In order to detect wood defects, the deep learning identification system is incorporated with the CNN architecture to allow the simultaneous learning of both feature extraction and image identification during the training. Furthermore, the CNN architecture has the ability to transform images into one-dimensional vectors and categorize them using an ANN by utilizing multiple channels for feature extraction [85].

In an article related to the identification of timber defects, Thomas [83] proved that utilizing a one-dimensional ANN to identify the grades of broadleaf trees yielded a greater accuracy of 80.2% compared to statistical approaches. Zeiler and Fergus [88] found that a two-dimensional CNN could outperform a commercial detector based on conventional feature descriptors and kernel SVM by a statistically significant margin (F_1 = 0.750 ± 0.018). Despite the fact that the CNN requires a large number of annotated datasets to attain a good prediction performance, transfer learning is often used to compensate for the data scarcity. According to the findings of visualising convolutional networks [89], the limited dataset would be sufficient for the last few layers to learn the features in the respective domains, as the model had obtained essential features such as corners in their first few layers. Hence, transfer learning has proven to be a very effective approach for the training of neural networks with a limited dataset. Additionally, implementing both transfer learning and data augmentation techniques in CNN does appear to be a viable approach in tackling limited dataset issues as well as improving CNN classification performance as demonstrated in [90]. A convolutional neural network (CNN) architecture is made up of three primary neural layers, namely a convolutional layer, pooling (subsampling) layer, and fully-connected layer [91]. With the current success of the implementation of the CNN in the computer vision domain, a number of well-known CNN architectures have been developed throughout the image processing field, especially with regard to the identification of timber defects as shown in Table 4. The AlexNet, VGG, and deep convolutional generative adversarial network (DCGAN) are among the architectures used in CNN to improve the accuracy of identification with their own configurations and contributions [92]. Urbonas [30] recommended the utilization of a faster region-based convolutional neural network to identify wood veneer surface defects, with the greatest average accuracy of 80.6% being achieved using a pre-trained ResNet152 neural network model. Nonetheless, a comparison of the CNN model to the SIFT+k-NN model [27] demonstrated the superiority of deep learning, with the CNN model achieving an accuracy of 88.09% for the identification of knots in contrast to its counterpart.

Table 4. Previous studies on wood defect identification using CNN architecture

Architecture	Reference
MobileNetV2	[42], [90]
ShuffleNet	[42], [90]
Deep convolutional neural network	[21], [88]
DenseNet	[40], [36]
GoogLeNet	[41], [93], [90]
LeNet	[40], [41], [94]
AlexNet	[30], [41], [93], [90]
VGG (16, 19)	[25], [30], [40], [93]
ResNet (18, 34, 50, 152)	[12], [26], [30], [42], [90], [93]
Other custom classifiers	[22]–[25], [27], [28], [95]

4. DISCUSSSION

This paper reviewed previous works on the automated inspection of timber surface defects, including various kinds of approaches targeting both the detection and identification of timber defects. While some of the approaches demonstrated good performance, most of them were still in the experimental phase. The majority of the challenges encountered during the industrial deployment of these approaches in small and medium-sized businesses were associated with high investment costs, and the AVI integrated with artificial intelligence appeared to be the most plausible approach owing to its ease of use and minimal operating costs. Although the capabilities of the AVI were limited to the inspection of surface defects, at the very least, they enhanced the inspection process. Nowadays, the trend is moving towards more contemporary machine learning/deep learning approaches, particularly in neural network architectures, for their outstanding performance. A brief comparison of contemporary algorithms and techniques for either the detection or identification of various wood defects was discussed. Machine learning and deep learning are the two types of artificial intelligence models used in the identification of timber defects. Although both learning models perform well in tasks involving parameter prediction and pattern identification, the chosen models are dependent on how data is provided to the system. Machine learning algorithms are designed to learn and increase their accuracy by analyzing labelled data, with the objective of producing further outputs with more sets of data. While the accuracy of machine learning improves with training, human intervention is required when the actual output changes unexpectedly. The deep learning algorithms, however, do not require human intervention as the nested layers in the networks put data through hierarchies of different concepts, which eventually learn through their own errors. Besides, the convolutional neural network architecture in deep learning models has proven its capabilities by producing record-breaking results on highly challenging datasets, while leveraging supervised learning [96]. For the identification of wood defects, feature extraction plays an important role in machine learning, where the extraction of characteristic quantities has a direct impact on the rate of image identification. Besides, a variety of feature extraction methods are available under digital image processing such as color, shape, and texture features [50].

The use of texture feature extraction methods such as the GLCM and LBP appears to be a viable option for timber images with rich textural details. Nevertheless, a proper parameter analysis of feature extraction techniques is important for ensuring well-characterized timber defect textural properties and high identification performance. It is worth mentioning that without effective feature extraction techniques and machine learning classifiers such as SVM and naïve Bayes, a high defect identification rate would be impossible. However, one of the major drawbacks of such methods (machine learning) is that precise models need to be developed to learn defect patterns, and they may still not be robust enough to respond to variations in the texture, lighting, and complexity of the defects. In contrast, the implementation of the CNN architecture in deep learning algorithms is one of the approaches for overcoming this disadvantage. While there are a number of classifiers that are used in machine learning, CNN architectures such as AlexNet are modifications of the ANN that use a unique set of max pooling layers and connected layers to construct the classifier. Although deep learning architectures yield the highest results, they are also the most computationally expensive compared to machine learning. In addition, CNNs are highly dependent on hardware and resources, where high amounts of random-access memory (RAM) and graphics processing unit (GPU) are required for extensive training processes. To summarize, striking a balance between a high accuracy rate and optimal computational resources in training models for the automated identification of wood defects remains an open research topic.

5. CONCLUSION

This review article provides an overview of wood defect identification using both machine learning and deep learning approaches. The article highlighted several machine learning studies that show exceptional classification performance despite having difficulty in determining the most suitable feature extraction method for wood defects. This remains a challenge for those who seek the best classification performance in wood defect identification using machine learning. While deep learning approaches have varied classification performance, it is worth noting that most of the feature extraction timber defect images are automatically deduced and tuned by the CNN architectures instead of the manual extraction and selection process as required by machine learning. This article describes the challenges and outlines the current trend in both machine learning and deep learning approaches along with several future directions that may be further explored in the identification of wood defects.

ACKNOWLEDGEMENTS

This research is supported by the Ministry of Higher Education (MOHE), Malaysia through Fundamental Research Grant Scheme (FRGS/1/2022/ICT02/UTEM/02/2) and Universiti Teknikal Malaysia Melaka.

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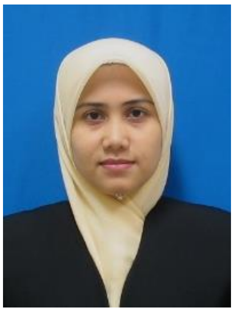

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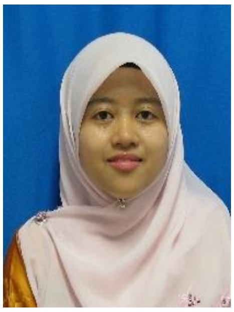

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