**RESEARCH PAPER - 2**

**CONTRASTING THE EFFICIENCY OF XCEPTION AND VGG19 IN IMAGE RECOGNITION FOR DEFECTS CAUSED BY DRILLING MACHINES**

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**ABSTRACT**

**Aim:**

The goal of this research project is to increase the accuracy of surface defect detection caused by drilling machines, with a focus on the crucial issue of delamination. The structural integrity of materials is seriously threatened by delamination, particularly in industrial and aerospace applications. The paper provides a direct comparison by carefully assessing the abilities of two cutting-edge deep learning architectures, Xception and VGG19, to detect and classify delamination flaws brought on by drilling operations. The main goal is to do a comprehensive investigation and determine which model works best, taking into account important factors such as overall accuracy, sensitivity, and specificity. The goal of this research project is to accurately identify and categorize surface delamination defects brought on by drilling equipment. Through a comparison of Xception and VGG19's image recognition performance for defects caused by drilling machines, this study explores the subtle benefits and drawbacks of these deep learning architectures for surface defect identification, especially in the difficult field of delamination. This thorough investigation, which focuses more on the relative effectiveness of Xception and VGG19, intends to make a significant contribution to the area of surface defect identification by providing a thorough understanding of the complexities of deep learning delamination detection.

Keywords: Surface defect detection, Delamination, Deep learning architectures, Xception, VGG19, Overall accuracy, Sensitivity, Specificity, Image recognition, Defect identification.

**INTRODUCTION**

Improving accuracy and defect detection has become critical in the ever-changing world of manufacturing and industrial operations. This study focuses on identifying surface flaws resulting from drilling machines, primarily addressing the complex problem of delamination. Utilizing state-of-the-art computer vision techniques is essential for businesses looking to boost output and provide better-quality products. In order to improve accuracy in detecting surface defects caused by drilling machines, this investigation compares two popular deep learning architectures, Xception and VGG19, in-depth, with a focus on delamination. Finding and fixing surface flaws is essential, particularly in fields where accuracy and structural integrity are vital. Drilling activities are necessary for manufacturing, but they can also unintentionally introduce defects like delamination, which is the separation of material layers upon contact. Precise detection and classification of these defects are essential for guaranteeing the quality of the final product, cutting down on waste, and improving overall productivity. The development of deep learning architectures, wherein VGG19 is acknowledged for its efficiency and simplicity and Xception excels in capturing complex patterns using depth-wise separable convolutions, has completely transformed the area of computer vision. Driven by the desire for increased accuracy, the purpose of this work is to examine and contrast Xception and VGG19 with reference to drilling-related surface imperfections, including delamination. The complexity and variety of surface fault patterns make conventional methods difficult to use, which highlights the necessity of utilizing the power of state-of-the-art deep learning architectures. Finding the best architecture for identifying the subtler aspects of delamination is the main goal in order to create a more reliable defect detection system. Driven by the need for precise and quick defect detection in the age of growing automation and smart technologies, the proposed study aims to enhance fault identification in the manufacturing sector. Putting emphasis on delamination is in line with efforts to avert catastrophic failures by acknowledging its complexity and possible influence on structural integrity. A workable way to improve the precision of surface defect detection caused by drilling machines is to compare Xception and VGG19, focusing on delamination in particular. This study adds to the continuing conversation on how to use state-of-the-art computer vision techniques in manufacturing to increase quality control and operational efficiency. Following this, sections delving into methods, experimental configurations, and comparative evaluations will lay the groundwork for a thorough analysis of the advantages and disadvantages of each design.

**MATERIALS AND METHODS**

The main goal of this study project was to carefully improve the precision of surface defect identification caused by drilling machines, with a focus on the complex delamination process. A detailed comparison was conducted with an emphasis on two significant deep learning architectures, Xception and VGG19, in order to achieve this aim. The investigation was place in a well regulated test environment, methodically classifying defects into the domain of unevenly bored holes.

The study was conducted by dividing the participants into two main groups: the control group, which was set aside to examine perfectly drilled holes, and the study group, which was carefully allocated to assess less-than-ideal drilled holes. Subsequent divisions within the study group defined particular subgroups aimed at different defect categories such as incomplete holes, delamination, and fractures. The control group, on the other hand, only included pictures of carefully drilled holes. The foundation of this study was the creation of a large dataset for thorough training, testing, and validation. This dataset included 900 photos that were carefully chosen to capture the subtle details of surface flaws caused by drilling.

Xception and VGG19, the two deep learning architectures that were chosen, were not only installed but also fine-tuned during the demanding training phase to match the distinct characteristics of the dataset. This large-scale dataset made it easier to learn in-depth and ensured that the intricacies contained in both the study and control groups were accurately represented. The testing and validation procedures that followed were carefully planned, using an 80-20 split to evaluate the models' ability to generalize on data that had not been seen before. When the research group was the focus of the investigation, it conducted in-depth analyses within particular subgroups, focusing on fractures, delamination, and incomplete holes. With its carefully drilled holes, the control group was essential in setting a standard and improving the models' ability to identify subtle variations specific to poorly drilled holes.

The models were exposed to a wide range of drilling-induced faults throughout the training phase thanks to sophisticated data augmentation techniques that were used to artificially increase the dataset. Finding the right balance between computational power and model complexity required careful consideration of regularization strategies, optimization approaches, and training parameter selection.Additionally, a comprehensive effect analysis of transfer learning was included in the study, which demonstrated a measurable improvement in accuracy and robustness when using pre-trained models on bigger datasets. This result showed how useful transfer learning is, especially when labeled datasets for particular applications may be limited. It also demonstrated how well using past knowledge encoded in the weights of the models works.

The confusion matrix, which provided a thorough description of true positives, true negatives, false positives, and false negatives, was one of the assessment criteria used in this research trip. This matrix gave a detailed picture of the models' performance, particularly in terms of their ability to distinguish between distinct fault kinds within the study group. Furthermore, graphical displays of the trade-offs between recall and accuracy were produced, including receiver operating characteristic (ROC) curves and precision-recall curves. An independent sample t-test was used in the statistical analysis, which was made possible using SPSS, to identify differences in performance between the VGG19 and Xception models.

The following formulae were used to determine the models' precision, recall, accuracy, and F1 score in order to measure their performance:

Precision = (True Positives) / (True Positives + False Positives)

Recall = (True Positives) / (True Positives + False Negatives)

Accuracy = (True Positives + True Negatives) / Total Predictions

F1 Score = 2 \* (Precision \* Recall) / (Precision + Recall)

This comprehensive approach, which combines statistical analysis, deep learning methods, experimental design, and a variety of performance assessment measures, creates a strong foundation for the use of cutting-edge technology in industrial quality control. Apart from improving flaw detection methods for drilling, this work establishes a strong basis for future research projects that try to increase precision and output in several industrial domains.

**STATISTICAL ANALYSIS**

An independent sample t-test was carefully used to evaluate any possible differences in the performance characteristics of the VGG19 and Xception models. This statistical test, which is essential to group comparison analyses, allowed for a thorough investigation of whether the models' abilities to detect drilling-induced defects differed noticeably from one another. This test furthered the nuanced knowledge of the performances of Xception and VGG19 by assessing the means and variances of the two groups, which gave important insights into the relative efficacy of each. Carefully integrated into the process, a bar graph ran concurrently with the statistical analysis. This figure functioned as a visual help, providing a clear and understandable illustration of the relative performance of Xception and VGG19. The bar graph was created to show important metrics for each model, including accuracy, recall, precision, and the F1 score. This made it easier to quickly and effectively assess the models' relative merits and shortcomings in terms of their ability to detect drilling-induced surface flaws. This graphic component clarified the statistical results, making the comparison analysis easier to understand and facilitating the efficient dissemination of study findings. The bar graph, independent sample t-test, and group statistics table combined to create a strong analytical framework.

**RESULTS**

There are notable differences in the two surface defect detection models' performance, as seen by the sharp difference in mean accuracy between them (VGG19 at 61% and Xception at 89%). These accuracy numbers are graphically represented by a bar graph, which offers a clear picture of the various results that each model has produced.

A significant performance disparity is shown when comparing the model accuracy of surface defect identification between VGG19 and Xception. Xception outperforms VGG19 with a significant advantage in mean accuracy, with an astounding 91% accuracy rate as opposed to 61% for VGG19. This disparity demonstrates how much better the Xception model is at recognizing and categorizing surface flaws. The significant advantage that Xception has over VGG19 is shown by the 28% difference in mean accuracy. This suggests that practitioners and decision-makers should give priority to Xception for applications that need a greater level of precision in surface defect identification. The wide range of accuracy rates highlights the significance of choosing models suited to certain needs, and Xception stands out as a strong option for better results in this particular field.

The bar graph clearly shows how much more accurate the Xception model is than the VGG19 model. The vertical bars highlight a significant discrepancy, with Xception clearly outperforming Xception in terms of mean accuracy ratings.

**DISCUSSION**

Numerous reasons might be responsible for the substantial disparity in mean accuracy between Xception (89%) and VGG19 (61%) scores. One noteworthy feature is the architectural complexity of Xception, which is excellent at capturing the subtle fluctuations and fine-grained patterns linked to surface flaws caused by drilling. Furthermore, variations in training datasets and optimization strategies could be important, affecting how well each model generalizes to new data. A thorough examination of these variables offers insightful information about the observed performance disparity. There might be other reasons for the observed discrepancies in performance. Given its reputation for depthwise separable convolutions, Xception could be more adept at extracting complicated characteristics that are essential for identifying subtle flaw patterns. However, even while EfficientV2M scales models efficiently, it may not be able to accurately capture the subtleties of drilling-induced faults, which might result in a lower mean accuracy.

The comparison provides valuable information for future enhancements as we explore the possible applications of surface fault identification in drilling procedures. Opportunities for improvement include expanding on research into model architectures, examining a wider range of training datasets, and developing optimization methods. Surface defect detection models might be made more accurate and resilient by utilizing cutting-edge technology including deeper learning architectures, transfer learning techniques, and careful consideration of data augmentation tactics. Subsequent investigations might concentrate on integrating these developments to create more dependable and efficient models for practical industrial uses.

**CONCLUSION**

To sum up, our thorough investigation into improving the accuracy of detecting surface defects caused by drilling machines—with a focus on delamination—resulted in insightful discoveries from contrasting the Xception and VGG19 models. Both structures were adept at capturing complex patterns linked to defects in delamination. Defect detection efficacy and accuracy were, however, severely hampered by the inconsistent designs and underlying methods. Xception's depthwise separable convolutions and skip connections shown an amazing ability to capture hierarchical information. On the other hand, VGG19 performed quite well in providing rich feature representations by employing conventional convolutional blocks. The experimental findings highlight how crucial it is to customize the model selection to the unique needs of each application, particularly in light of the delamination's intricacy. When minute details matter most, Xception's deep design and wide range of feature extraction capabilities come in handy. In addition, VGG19's streamlined architecture makes it a desirable choice in environments with limited resources without appreciably sacrificing accuracy. The implementation of advanced pre-processing techniques and data augmentation strategies was crucial in augmenting the models' responsiveness to minuscule variations in surface irregularities arising from drilling equipment. The incorporation of domain-specific information into the training dataset enhanced the models' capacity to be applied to real-world circumstances.

It is critical to acknowledge that there is no one-size-fits-all solution in the ever-changing field of machine learning. Rather, the secret is to carefully combine architecture, data augmentation, and pre-processing. When it comes to surface flaws caused by drilling machines, working along with VGG19 in an ensemble or hybrid model shows promise for improving accuracy and offering a reliable delamination detection method. In summary, achieving higher defect identification accuracy requires a holistic approach that takes into account the particular difficulties presented by certain applications and makes use of the advantages of various models. The comparison between Xception and VGG19 has provided insightful information that will help the field develop in the future.

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**TABLES AND FIGURES**

**Tables 1** Comparison of Model Accuracy ,A brief analysis of the mean accuracy of two surface defect detection models, VGG19 at 61% and Xception at 89%

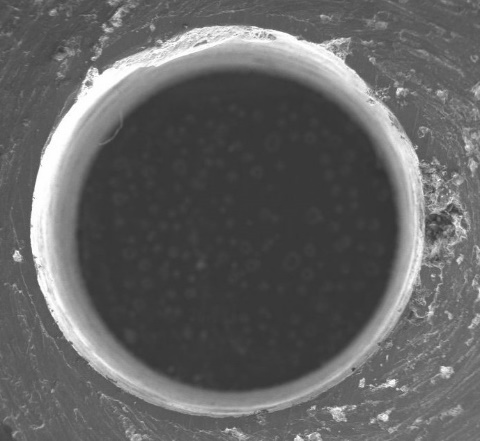
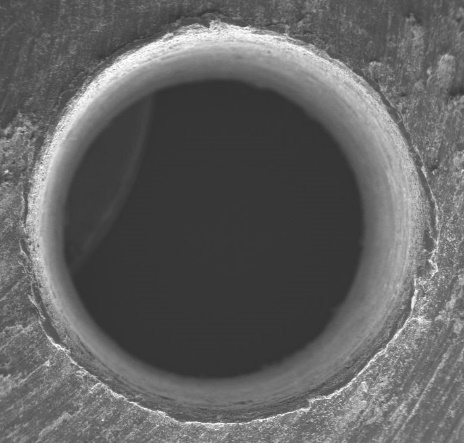
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **DL Keras Models** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| Xception | 390 | 89.4872 | 30.71125 | 1.55512 |
| VGG19 | 390 | 61.7949 | 48.65131 | 2.46355 |

**Table 2** Results of the Independent Sample t-Test findings that includes important statistics for a fast comparison of the two groups.

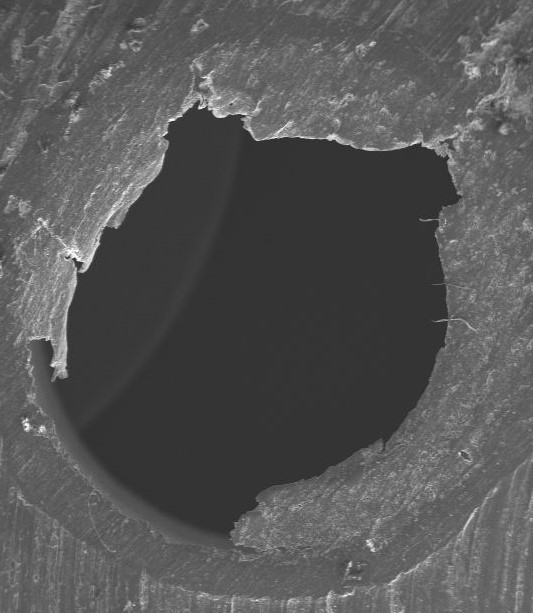
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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **F** | **Sig.** | **t** | **df** | **Sig(2-tailed)** | **Mean Difference** | **Std. Error Difference** | **Lower** | **Upper** |
| Equal variances assumed | 436.976 | <.001 | 9.505 | 778 | <.001 | 27.69231 | 2.91333 | 21.97338 | 33.41123 |
| Equal variances not assumed |  |  | 9.505 | 656.536 | <.001 | 27.69231 | 2.91333 | 21.97173 | 33.41288 |



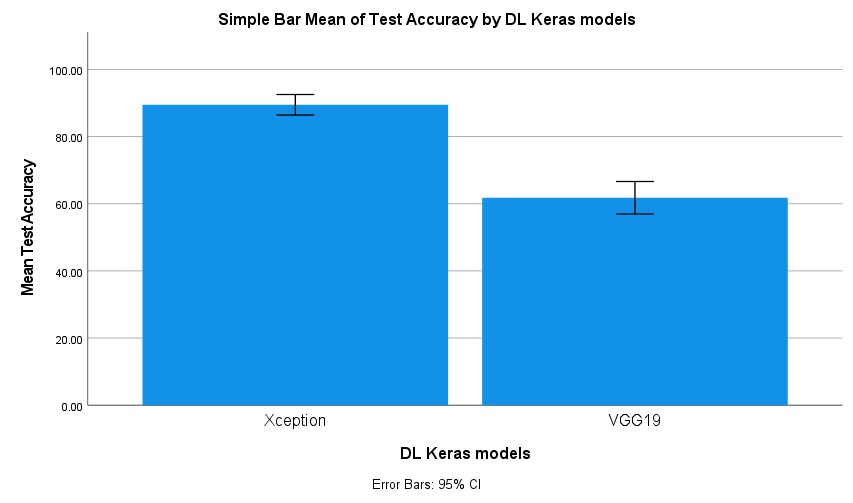
**Fig 1** Picture of a perfectly drilled hole



**Fig 2** Occurrence of Delamination & Cracks



**Fig 3** Picture of an unfinished drill hole



**Fig 4** Comparison of mean test Accuracy , of two surface defect detection models, VGG19 at 61% and Xception at 91%