OPTIMIZING FAILURE MODE ANALYSIS OF DENTAL RESTORATIVE MATERIALS: BALANCING EFFICIENCY AND ACCURACY

Bérangère Cournault *† *Luc Vedrenne* *‡ *Teyagirwa Prudence Felix* † *Erkel Arnaud* †
Hattenberger Grégoire † *Jmal Hamdi* ‡ *Kharouf Naji* † *Etienne Olivier* †

† Biomaterials-bioengineering, Inserm UMR 1121, University of Strasbourg, France
‡ ICube, UMR 7357 CNRS, University of Strasbourg, France

ABSTRACT

To quantify the adhesion of ceramics to dental hard tissues, macroscopic shear bond strength (SBS) tests are commonly used. A failure mode analysis is then performed to determine the location of the failure and its correlation with the corresponding SBS values. Most analyses in the literature use an optical microscope. In this work, we introduce a new approach to perform objective and efficient failure mode analysis using a weakly supervised deep neural network. Our experimental results demonstrate that this approach significantly outperforms human analysis.

***Index Terms*—** Optical microscopy, Shear bond strength tests, Deep neural network, Weakly supervised learning, Failure mode analysis.

1. INTRODUCTION

To assist clinicians in selecting reliable adhesive systems and ceramics for dental restorations, laboratory tests can be conducted. Bond strength is one such test that can predict, to some extent, the longevity of a bond [1]. It can be assessed by tests involving forces (shear or tension) applied to the interface between ceramic, adhesive system, and tooth, until mechanical breakage [2] [3].

These tests result in the failure of the restorative material, adhesive system and dental substrate assembly. Therefore, a microscopic analysis must follow to determine the mode of failure that occurred on each sample (Fig. 1). An adhesive failure happens at the interface between the adhesive system and its substrate (the restorative material or the dental substrate), while a cohesive failure occurs within one of the materials. If a failure occurs both at an interface and inside one of the materials, it is referred to as a mixed failure [2] [3] [4].

There is no consensus in the literature on how to perform failure mode analysis [2] [5]. Most authors use an optical microscope (OM), which may introduce misinterpretations [5]. Therefore, other authors use scanning electron microscopy (SEM) to identify the failure mode [4][6]. However, this method is time-consuming due to sample preparation and is not suitable for screening new formulations. For this reason, some authors combine both methods. The samples are initially screened using OM at 20x to 40x magnification. Then, three [7] or two [8] [9] representative specimens per test group, or one representative specimen of each mode of failure [10], are chosen for analysis under SEM. Although profilometers present an alternative methodology, their utilization is hampered by the time-consuming nature of sample analysis. Furthermore, the scarcity of biology laboratories equipped with this technology poses a practical limitation on its widespread application.

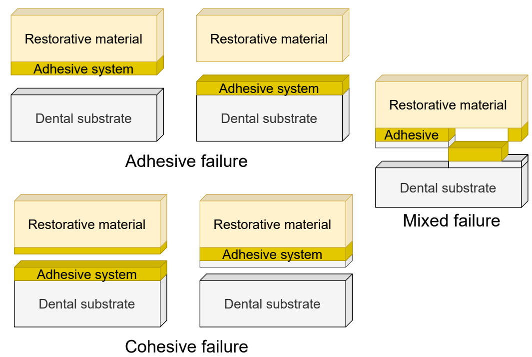


Fig. 1. Modes of failure of ceramic bonded to teeth [3]

The aim of this work is to assess the combined OM and SEM analysis, and to propose a new approach to conduct an efficient and reliable failure mode analysis that doesn't require SEM data, based on a deep neural network operating on OM data.

2. MATERIALS AND METHODS

2.1. Sample preparation

Human cavity-free teeth, extracted for periodontal reasons, were used in this study. They were trimmed to an approximately 8 mm diameter flat area of enamel or dentin based on

*Equal contribution

their study group. Each tooth sample was embedded in a 20 mm diameter, 3 mm high self-curing resin disc. Dental substrate roughness was standardized using a 600-grit sandpaper on a manual polisher. All samples were stored in a physiological sodium chloride solution (0.9% NaCl) until bonding. Ceramic blocks were milled into 5 mm diameter cylinders, and the adhesive systems used varied across studies. Adhesion was performed according to each adhesive system's manufacturer recommendations (Fig. 2). The resulting samples were stored in distilled water recipients for 7 to 150 days, depending on the study group.

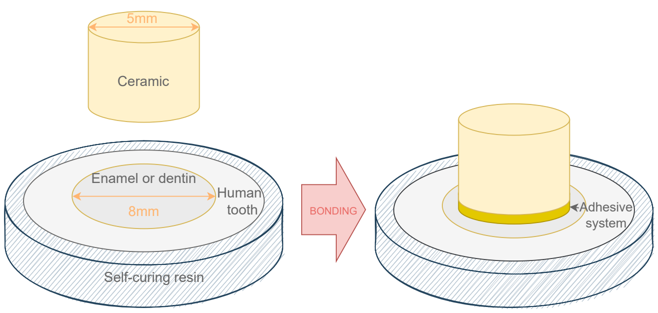


Fig. 2. Sample preparation

The samples underwent a macroscopic shear bond strength (SBS) test using an Instron 3345 universal testing machine (Fig. 3), according to ISO 29022:2013 guidelines [11]. The maximal SBS, which was determined by measuring the shear force until failure, was used as a quantitative measure to evaluate the adhesion properties.

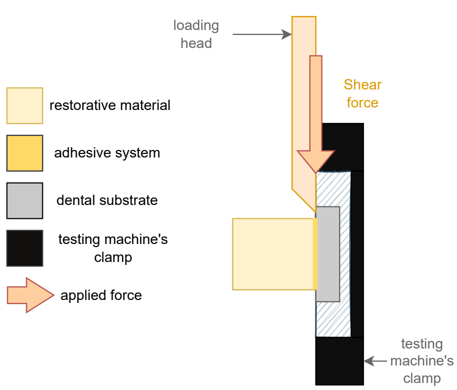


Fig. 3. Macroscopic SBS-test

We obtained 155 samples using various ceramics, adhesive systems, and dental hard tissues. This sample diversity provides a strong testbed for evaluating the generalizability of different analysis methods.

2.2. Failure mode analysis using optical microscopy

Images of each failure interface, 155 for the dental side and 155 for the ceramic side, were taken using a numerical optical microscope (VHX 5000, Keyence, Japan) at 100x magnification. The images were then circularly cropped to isolate the bonding area. Two independent observers analyzed 80 samples using only OM images, following conventional literature methods. In case of discrepancies, they reanalyzed samples until reaching a consensus on classification.

A sample is classified based on the class that occupies over 75% of the failure area [2]. If no single class exceeds 75%, the sample is labeled as a mixed failure. Interactive segmentation [12] was employed to generate multi-target masks for precise quantification of the pixel distribution and accurate calculation of the proportion of each failure mode within a given sample (Fig. 4).

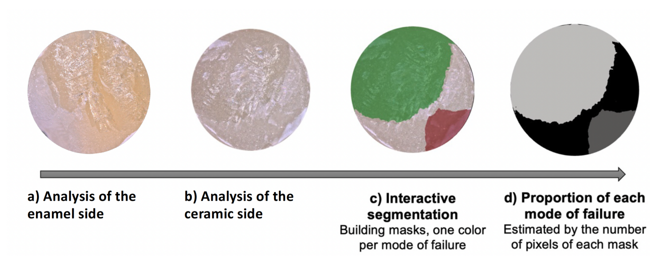


Fig. 4. Determining the proportion of each mode of failure

2.3. Failure mode analysis using optical microscopy and scanning electron microscopy for representative samples

Two representative samples from each group of the same 80 were selected for scanning electron microscopy (SEM) analysis. The examination started with the ceramic side, exempt from prior dehydration. In cases where the failure mode classification was unclear, the analysis was extended to the dental side. SEM images were captured using a Quanta 250 FEG SEM (FEI, Netherlands), at 30x magnification to include the entire bonding area in a single frame. An example is shown in Fig. 5 for a specimen of glass-ceramic coated zirconia bonded to enamel with Panavia V5 (Kuraray, Japan).

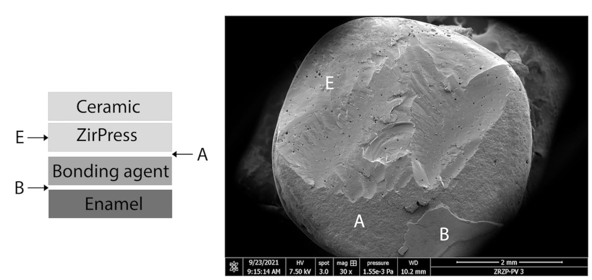


Fig. 5. Failure mode analysis of a ceramic-side using SEM

Adding this information to the process detailed earlier (Sec. 2.2), the observer compared OM images with corresponding SEM images, drawing analogies to enhance identification of failure modes. This analysis helped to construct more accurate masks for precise calculation of each failure mode's proportion through interactive segmentation.

2.4. Building the ground-truth for our dataset : Failure mode analysis using focus-variation microscopy

The dental sides of the 155 samples were imaged in 3D using a focus-variation microscope (InfiniteFocus SL, Bruker Alikona, Grambach, Austria). This profilometry technique combines the small depth of focus of an optical system with vertical scanning to provide a 3D image with topographical and color information [13]. The method ensures sharp focus for each region of the sample, using a x10 objective, and achieving a vertical resolution of 100 nm.

After trimming the dental sides of the samples prior to ceramic bonding (Sec. 2.1), the bonding surface aligns with the surrounding resin. Following the SBS test, the resin level remains unchanged, allowing us to establish the focus-variation microscope scale origin at the resin level. A dental surface at the origin level signifies an absence of adhesive system, indicating adhesive failure to enamel or dentin. A negative relief indicates dental tissue loss, signaling cohesive failure within the tooth. A positive relief suggests that an adhesive system layer remains on the dental substrate, which could be due to either adhesive failure to ceramic or cohesive failure within the adhesive system. Fig. 6 exemplifies this analysis method. In the latter case, surface roughness analysis can help distinguish between failure types, similar to SEM image analysis [14] [15]: a flat surface with ceramic milling marks indicates adhesive failure to ceramic, while a rough surface indicates cohesive failure within the adhesive system.

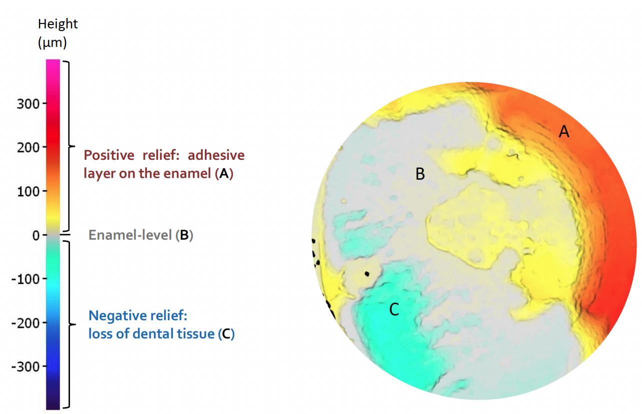


Fig. 6. Failure mode analysis using focus-variation microscopy

The examination of the dental side using focus variation microscopy provided strong evidence for classifying failure modes. To validate and improve this, a thorough verification process was applied to the corresponding ceramic side, utilizing OM and SEM on two representative samples per group. As a result, 155 samples were labeled on both the dental and ceramic sides in OM images.

The dataset excluded the lone occurrence of cohesive failures within the dental substrate, resulting in a streamlined classification system of four distinct classes: Adhesive to the dental substrate, Adhesive to ceramic, Cohesive within the adhesive system, and Mixed failure. It is important to note that this study primarily serves as a proof of concept, demonstrating the feasibility of training a neural network for failure mode classification based on optical microscopy.

2.5. Failure mode analysis using a neural network

We train an EfficientNet-B3 [16] convolutional neural network on our dataset using supervised learning. To assess the model's effectiveness, we reserved 20% of the data as a validation set, not utilized during training. Challenges in the task stem from limited data and class imbalance. To address potential overfitting and bias arising from these issues, we employ a network pre-trained on ImageNet. Additionally, the network's ability to learn from such a small dataset is enhanced by implementing various regularization techniques: data augmentation, label smoothing [17], mixup [18], cutmix [19], and stochastic weight averaging [20].

3. RESULTS

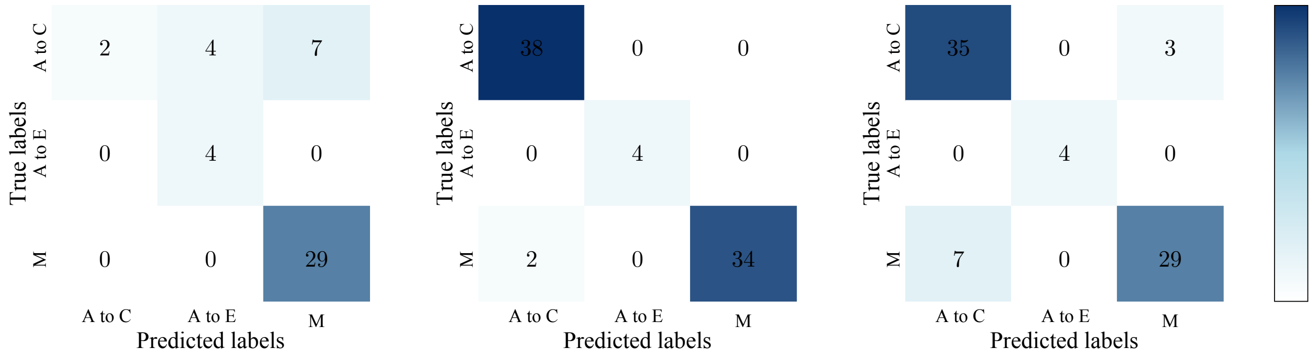
Performances are measured using the F1 score, which is the harmonic mean of the precision and recall. It can be computed as

$$\frac{2\,\mathrm{TP}}{2\,\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}, \tag{1}$$

where TP, FP and FN stand for True Positive, False Positive and False Negative respectively. The performance of the three methods is shown in Tab. 1. The human observers, relying solely on optical microscopy (OM), demonstrated a moderate F1 score of 45.47 for failure mode detection. However, the observer's capability was significantly boosted by the introduction of scanning electron microscopy (SEM) alongside OM, yielding a F1 score of 97.43.

Meanwhile, the neural network on OM achieved a commendable F1 score of 87.12, albeit slightly below the integrated SEM and OM performance.

Observers relying on OM faced a challenge in distinguishing the adhesive to ceramic class due to the absence of SEM analysis. This resulted in 25 instances of confusion with cohesive failure, as shown in Fig. 7.a. Despite this, their proficiency in identifying mixed failures remained high, with 29 out of 36 cases correctly recognized. In contrast, when using OM and SEM on two representative samples per group,



(a) Human observer on OM (b) Human observer on OM + SIM (c) Neural network on OM

Fig. 7. Human observers on optical miscropy

Analysis method	F1 score
Human observer on OM only	45.47
Human observer on OM + SEM on representative samples	97.43
Neural network on OM only	87.12

Table 1. Performance of the three compared methods

observers made only 2 errors, specifically misclassifying 2 mixed failures as adhesive to ceramic (Fig. 7.b). The neural network, which was applied to the same 80 samples using only OM, demonstrated precision in avoiding misclassification of adhesive to the dental substrate failures (Fig. 7.c). However, like human observers using OM and SEM on representative samples, the neural network exhibited confusion between adhesive to ceramic and mixed failures.

4. CONCLUSION

Optical microscopy is a commonly used method for failure mode analysis in literature, despite its acknowledged limitations. In this study, we quantified this error and yielded an F1 score of 45.47. The observers had difficulty with classifying adhesive failure to ceramic.

Although it is desirable to scan all samples with SEM for comprehensive failure mode identification, the practical value of a macroscopic SBS test lies in its ease of use and rapid screening capabilities for new formulations or bonding protocols. Within the constraints of this study, combining OM with SEM on two representative samples per group appears to be a reliable method, with an F1 score of 97.43, and is more time-efficient than a complete SEM analysis.

The unexpectedly high F1 score of 87.12, given the study's dataset and human observers performance, suggests that the OM-only classification task is potentially easy for a convolutional neural network. This indicates the task's potential for further development. The primary limitation is the scarcity of cohesive failure samples, which could be addressed by expanding the training set.

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6. COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that the study does not involve human- or animal-derived samples that require ethical approval. This article does not contain any studies involving human participants performed by any of the authors.

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