Classification of Tooth Decay by Computer-Aided Diagnostics using Laser Speckle Image Analysis

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ABSTRACT
Dental caries is one of the most prevalent diseases in the world, affecting almost the entirety (100%) of the population, generating a great concern in oral health. Its early detection - before the need for invasive restoration procedures - contributes to the general well-being of the population. This work demonstrates the detection and classification of early carious lesions with an ICDAS (International Caries Detection and Assessment System) lower than 1. For this work, we used 45 samples of bovine incisors that were cut, polished, and inserted in a PVC holder. Each sample had half of its surface covered and the other half subjected to an acid etching process producing a carious-like lesion. The samples were illuminated with laser light and imaged. After a pre-processing all images were classified according to the severity of the lesion and a neural network was trained to detect and quantify the lesions. With this approach we obtained over 83% accuracy for the detection of the lesion and over 63% of accuracy for the classification of the lesions that were considered an ICDAS lower than 1 by atrained dentist.

Keywords
Laser, speckle, image, Artificial Neural Networks, decay, carious lesions

1. INTRODUCTION
The tooth is the hard organ found in the mouth of the human being and many animals and with the function of chewing food or defense (in the case of certain animals). They are mineralized and hard tissue structures, the outer part of which is known as enamel (harder) and the inner part known as dentin (less hard).

Dental enamel is a highly mineralized structure, consisting of crystals of carbonated and sometimes fluoridated hydroxyapatite (HA). HA is a crystal formed by calcium phosphate and has a dynamic relationship with saliva, which is an organic fluid made up of calcium and phosphate ions. [1]

The basic unit of the enamel is called prism. Measuring 4 µm - 8 µm in diameter, an enamel prism is a small, compact cluster of hydroxyapatite, making up a complex arrangement,

1.1 Decay
Dental caries is defined by the World Health Organization (WHO) as "a localized pathological process, of external origin, which begins after tooth eruption, determines a softening of the hard tissue of the tooth and progresses to the formation of a cavity". This is one of the most prevalent diseases in the world, affecting almost the entirety (100%) of the population, generating a great concern in oral health. Its early detection - before the need for invasive restoration procedures -contributes to the general well-being of the population.

It is considered a complex and multifactorial disease, which determines the localized destruction of mineralized tissues. It is also influenced by the time factor and is described as a process dependent on the interaction between specific microbiota, carbohydrates, and a susceptible tooth surface. Disease progression is slow, resulting from an imbalance between the mineral in the tooth and the plaque substrates (biofilm) present in this tooth, causing a mineral loss. [2]

Caries are not self-limiting and can destroy the dental element if not treated, thus observing the importance of early diagnosis of the clinical signs of the disease [3]

It is mediated by the presence of bacterial plaque, which will only be considered cariogenic occurring during a certain period with interactions of several factors in critical conditions [4]

The factors that can interact and determine the presence of caries disease are classified into microorganism, host, and substrate considered the main factors, and secondary factors classified as modulators, saliva, and fluoride exposure when carbohydrates are ingested, they are metabolized by microorganisms, and lactic acid is produced, causing a drop in pH to critical levels (pH < 5.5) and dissolution of HA crystals. In this situation, the physicochemical tendency becomes the opposite, the loss of minerals from the tooth to the environment, the saliva, starting the demineralization process. From this unbalanced De-Me (demineralization and mineralization) process, the incidence of caries onset occurs. With further demineralization, the enamel becomes porous and the spaces created between the hydroxyapatite crystals are filled with water. [5]

Knowing that the refractive index of hydroxyapatite crystals is 1.62, that of water is 1.33, there is a similarity between the refractive index of water and HA, and clinically, the observation may go unnoticed this occurrence. With drying, the water between the crystals is removed and replaced by air, which has a lower refractive index, the lesion takes on a clinically whitish and opaque appearance, determining the 1st clinical sign of the lesion of caries disease: the opaque white spot. – ICDAS 1 - also called a non-cavitated or incipient lesion. The International Caries Detection and Assessment System (ICDAS) is a method of clinical caries assessment ranging from ICDAS 0 as healthy tissue, ICDAS 1 as Remarkable opacity after drying – "Dry white spot", ICDAS 2 as notable opacity in the presence of moisture - "wet white spot" and from ICDAS 3 to ICDAS 6 as enamel and dentin cavitation indicated by the degree of intensity. [6]

The caries lesion generates a mineral loss in the affected tissue, which results in changes in the roughness and consequently, in the optical properties, however, visual inspection is still the most commonly used method for the diagnosis of caries lesion (Gold Standard), mostly using the ICDAS index. However, it is a subjective examination, and the use of objective and quantitative methods should be indicated for a better diagnosis and monitoring of these lesions. [7]

1.2 Laser Speckle

The laser produces a coherent beam of light, meaning it is in phase, collimated (parallel propagation) and monochromatic unlike other incoherent light emissions where photons propagate randomly and in all directions.

Due to the property of coherent light, the image of the scattered light from a laser on a given object (known as laser speckle image - LSI - or simply speckle) has a unique optical pattern that is impossible to be mimicked by a non-coherent light source.

This phenomenon occurs by the reflection of different distances of the optical path of the beam on the surface illuminated in the object.

The interference patterns formed by the speckle image occur due to the phase difference of the scattered light beams, making the image full of dark and bright spots. Despite the random nature of the speckle, it contains information on the surface[8].

This pattern obtained by the refraction of coherent light in the different optical paths is more sensitive to the surface properties of the illuminated object, such as roughness; texture, and edges than the pattern caused by lighting with a light source not coherent with random waves. In other words, the pattern of coherent light scattering by an object is sensitive to the smallest changes in the surface and even the subsurface of the object.

Despite having a random character, information can be extracted from this granulate in the context of Statistical Theory [8]

Works on laser speckle images are already well known in the literature, but predominantly these studies and use are in dynamic speckle or the temporal domain, that is, speckle (optical granules) in motion processes are analyzed,[9, 10]

Our study is already carried out in static mode or the spatial domain, we analyze the speckle (optical granules) in their characteristics, (brightness, contrast, sharpness, and their statistics) fixed and static. [11]

DEANA et al in 2013 presented a study on laser-illuminated teeth (speckle) where through first-order spatial statistics applied to the image the detection of caries lesions on the enamel surface occurred, Deana emphasizes in this study on the speckle in the image of the tooth is in the space domain, that is, the absence of tissue movement and not in the time domain, where there are more studies in the health sciences where they analyze the movement and speed of particles in the images obtained by Speckle.[11]

The work was continued by KOSHOJI NH. in 2014, who studies dental erosion and again obtains good results in first-order statistics on speckle images in the qualification of the lesion, thus achieving a quantification of progression [12, 13]

In 2016 SILVA JVP., carried out a work on speckle images in incipient caries lesions, below ICDAS 1, where through first-order statistics he managed to ANSARI *et al p*resented an approach using 3D digital photography techniques caries lesions taken from speckled images. [14, 15]

Gavinho*et al*also conducted works on detecting White spot lesions using laser speckle image segmentation and computer vision methods [16, 17]

1.3 Machine learning

For our study of speckle teeth images, we used Artificial Intelligence techniques. This makes it possible for AI to identify new patterns and make decisions on the classification of the images.

After pre-processing all the images and their classification according to the severity of the lesion, we trained the artificial neural network.

Principal component analysis, or PCA, is a dimensionality reduction method often used to reduce the dimensionality of large data sets by transforming a large set of variables into a smaller one that still contains most of the large set's information.[18]

Reducing the number of variables in a dataset naturally comes at the expense of accuracy, however, simplifying the dataset makes it easier to explore and visualize and makes data analysis much more agile for machine learning algorithms. [18]

Principal components are new variables constructed as a linear combinations or mixtures of the initial variables. These combinations are made in such a way that the new variables (*ie*, principal components) are uncorrelated and most of the information within the initial variables is compressed into the first components. Therefore a 0-dimensional data gives you 10 main components, but PCA tries to put as much information as possible in the first component, as much remaining information as possible in the second, and so on. [18]

An important thing to mention that the principal components are less interpretable and have no real meaning since they are constructed as linear combinations of the initial variables. [18]

To our knowledge, this is the first work that demonstrates the detection and classification of early carious lesions with an ICDAS lower than 1.

2. MATERIAL AND METHODS

2.1 Samples

For this work, we used 45 samples of bovine incisor randomly divided into 3 groups. We chemically induced a lesion similar to the initial stages of caries commonly called white spot (wet or dry) at different stages.

For each sample, a fragment of the buccal surface of a bovine incisor tooth of 4 x 6 mm (minimum) was obtained and included in a PVC tube with acrylic resin, leaving the dental enamel exposed in a flat and parallel.

Each sample was polished using water sandpaper with different grains from 600 to 2000 sanded in a belt sander, orbital sander, and in the smallest granulations in a manual procedure. After flattening, they were manually polished with grinding liquid (3M Polishing Liquid - n° 3), Two regions were created in the bovine teeth samples: a control region (healthy region - ICDAS 0) that will remain unchanged and another region where a white spot similar to an initial caries lesion will be artificially induced (dry white spot or wet white spot)

For the induction of caries-like lesions, we used the methodology that was proposed in [19]

We induced a lesion similar to caries (white spot) performing an acid etch rich in hydroxyapatite in half of the sample, the other half is protected by an adhesive tape keeping the surface in its original state (ICDAS 0) to obtain the comparative results with the decayed region.

We placed the 3 groups of samples separated and immersed in 50 ml of a demineralizing solution (pH 5.0) containing 0.05 M of acetate and hydroxyapatite buffer solution at 50% saturated with enamel powder for 24, 48, and 72 h 37 °C respectively.

To prepare the solution, enamel powder (74 to 105 µm particles) was stirred in 0.05 sodium acetate buffer solution at pH 5.0 for 96 h at 37 °C (0.50 g/l). The solution was used in a ratio of 2.0 ml/mm2 of exposed enamel area.

After the lesion induction process, we removed the tape and washed the samples with Milli-Q water.

2.2 Experimental setup

To obtain the laser speckle image, each sample was illuminated with a red laser diode (custom-made Biolambda) with a wavelength of 650 nm. We placed the laser at approximately 12 cm from the sample and a lens was positioned to expand the illumination area, obtaining uniform visible illumination of the entire region of interest in the sample (10 mm). Both regions of dental enamel (healthy and injured) were illuminated simultaneously. The laser-illuminated image was captured by a color CMOS digital camera with images captured in RGB RAW mode (Canon EOS Rebel T3i) at approximately 9 cm from the sample. The camera was set with a shutter speed of 1/4000, lens aperture at F5.6, and photographic sensitivity ISO100 for the best possible contrast. A Canon 100 macro lens was attached to the camera. The schematic diagram of the experimental arrangement can be seen in Figure 1

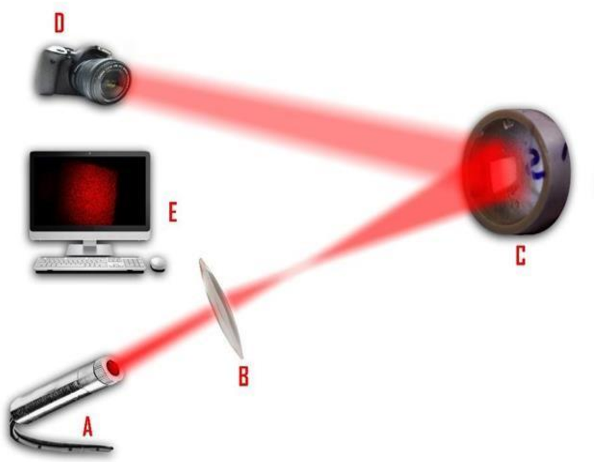

Fig:1 Schematic diagram of the experimental setup used in this work: A) Semiconductor laser source, B) beam expander, C) sample with sound-decay region D) Digital camera E) ANN analysis software

2.3 Pre-processing and classification of the images

With the image bank of the samples, two regions of interest were manually selected, these respective chosen areas were subdivided into 4 x 4 pixels windows and transformed into a set of vectors. With this set of raw data vectors, from the speckle image, the qualifiers that indicate the healthy area and the injured area and the respective time of the caries chemical induction process, 24, 48 or 72 hours, were added, as shown in Figure 2.

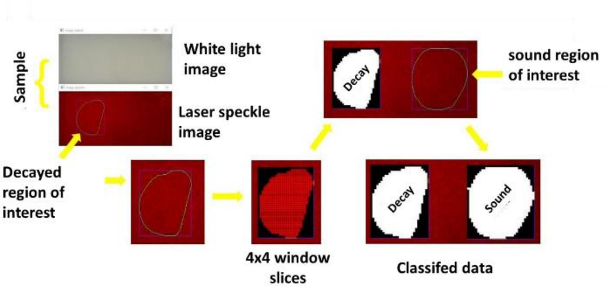

Fig. 2: pre-processing and classification of the image procedure

2.4 Statistical features

Based on the raw data (4 x 4 pixels = 16 values), we calculated 19 statistical features as demonstrated in Table 1

Table 1:Statistical features added to the data

Feature	Equation
1st order moment	$m_1 = \frac{1}{n}\sum x$
2nd order moment	$m_2 = \frac{1}{n}\sum (x-\bar{x})^2$
3rd order moment	$m_3 = \frac{1}{n}\sum (x-\bar{x})^3$
4th order moment	$m_4 = \frac{1}{n}\sum (x-\bar{x})^4$
6th order normalized moment	$m_6 = \frac{1}{n * m_2}\sum (x-\bar{x})^6$
1st order cumulant	$c_1 = m_1$
2nd order cumulant	$c2 = m_2 - m_1{}^2$
3rd order cumulant	$c3 = m_3 - 3m_1m_2 + 2m_1{}^3$
4th order cumulant	$c4 = m_4 + m_3m_1 - 3m_2{}^2 + 12m_2m_1{}^2 - 6m_1{}^4$
Distortion	$= \frac{m_3}{\sqrt{m_2{}^3}}$
Kurtosis	$= \frac{m_4}{\sqrt{m_2^4}}$
Absolut mean	$\lvert\bar{x}\rvert = {}^1/n \sum\lvert x\rvert$
Peak value	$x_p = max\lvert x\rvert$
Absolute square root	xrms$= \left({}^1/n \sum \sqrt{\lvert x\rvert}\right)^2$
Root mean square	$= \sqrt{\frac{1}{N}\sum (x-x)^2}$
Crist factor	$= x_p/x_{rms}$
Shape factor	$= \frac{x_{rms}}{\lvert\bar{x}\rvert}$
Standard deviation	$sd = \sqrt{\frac{\sum (x-\bar{x})^2}{n-1}}$
Lasca (Laser speckle contrast analysis	$= sd/m_1$

2.5 Experimental datasets for the neural network

Neural networks were trained with the following data inputs:

- Set of vectors using raw data only classified as healthy - SD and decayed,
- Set of vectors using raw data only classified as sound – SD; decayed 24h,; decayed 48h; and decayed 72h;
- Set of statistical data vectors only classified as sound – SD; decayed 24h; decayed 48h; and decayed 72h;
- Set of raw and statistical data vectors classified as sound – SD; decayed 24h; decayed 48h; and decayed 72h;
- Set of vectors statistical and raw data with reduced dimension by PCA (with 5 components) classified as sound – SD and decayed.
- Set of statistical and raw data vectors with reduced dimension by PCA

3. RESULTS

After parameterizing the Neural Network, (numbers of hidden layers, numbers of neurons of the hidden layers, the number of iterations (epoch) for better accuracy, we performed the training and test in the databases and obtained the following results.

Initially, using only the raw data, we divided the data into neighbor pairs to analyze the response of the ANN to data with values in proximity. The results are shown in Table 2

Table 2: Accuracy of the ANN when classifying decays with similar severity

Sound X 24h	24h x 48h	48h x 72h
86,50%	74,82%	57,26%

In our second trial, we grouped all the decay groups into one dataset and trained the ANN to detect the presence of the decay using only the raw data as input (no statistical features were added). Such results are in Table 3

Table 3: Confusion matrix of the raw data classified only as sound or decay

Classification \ Prediction	Decay	Sound
Decay	6177	1142
Sound	1365	5761

Correctclassified: 11938 WrongClassified: 2507

Accuracy: 82.645% Error: 17.355%

Table 4 shows the Confusion Matrix obtained using the PCA with the raw data plus its statistical characteristics grouped only as decay and sound tissue.

Table 4: Confusion matrix of the raw data plus the statistical features and PCA classified only as sound or decay

Classification \ Prediction	Decay	Sound
Decay	6163	1202
Sound	1348	5732

Correctclassified: 11895 WrongClassified: 2550
Accuracy: 82.347% Error: 17.653%

Table 5 shows the Confusion Matrix obtained using only the raw data divided by acid each duration

Table 5: Confusion matrix of the raw data separated by the acid etch duration

Classification \ Prediction	Sound	24h	48h	72h
Sound	6377	8	436	378
24h	499	1	265	146
48h	430	3	2200	557
72h	909	3	1573	660

Correctclassified: 9238 WrongClassified: 5207
Accuracy 63.953% Error: 36.047%

Table 6 shows the Confusion Matrix obtained using only the statistical features of the data divided by acid etch duration

Table 6: Confusion matrix of the statistical features separated by the acid etch duration

Classification \ Prediction	Sound	24h	48h	72h
Sound	6352	0	429	362
24h	518	0	254	150
48h	544	0	1975	724
72h	990	0	1441	706

Correctclassified: 9033 WrongClassified: 5412
Accuracy: 62.534% Error: 37.466%

Table 7 shows the Confusion Matrix obtained using the statistical features plus the raw data devided by acid etch duration

Table 7: Confusion matrix of the raw data plus the statistical features separated by the acid etch duration

Classification \ Prediction	Sound	24h	48h	7
Sound	6407	6	464	357
24h	502	2	282	116
48h	437	7	2106	511
72h	994	3	1584	667

Correctclassified: 9182 WrongClassified: 5263
Accuracy: 63.565% Error: 36.435%

Table 8 shows the Confusion Matrix obtained using the PCA of the statistical features plus the raw data divided by acid etch duration

Table 8: Confusion matrix of the PCA of the raw data plus the statistical features separated by the acid etch duration

Classification \ Prediction	Sound	24h	48h	7
Sound	6315	4	461	393
24h	544	4	263	144
48h	515	3	2011	611
72h	1004	3	1482	687

Correctclassified: 9017 WrongClassified: 5428
Accuracy 62.423% Error: 37.577%

4. DISCUSSIONS

Normal or Body We found that under non-coherent lighting, the contrast intensity between the decayed enamel region to the sound one is slightly higher therefore, the contrast is weak thus, even a well-trained and experienced dentist would have difficulties detecting it. However, in the image obtained illuminated by a laser, this contrast is evidenced, facilitating, therefore, the detection of the lesion, even in its initial stages this technique was able to determine the presence or absence of the lesion.

Table 1 shows that the ANN can easily discriminate sound tissue from decayed tissue even by analyzing only the raw data. Such accuracy isn't when comparing two decays with different severities (in theory). When the decay is first installed, there is a notable change in the microstructure of the enamel, leading to a difference in the light propagation in the affected area, which can be observed by a trained dentist. Meanwhile, a slight increase in the severity of the lesion is much harder to identify even by an experienced dentist.

The injuries of this work are very incipient, considered sub-clinical. This type of lesion does not require any destructive intervention by the health professional, only guidance and an eventual topical application of fluoride, being often undetectable in clinical practice. However, this work was still able to detect the lesion with an accuracy of 82.3%

It is important to mention that, although we were trying to mimic ICDAS 1 and 2 lesions, in the clinical practice the 24h group was hardly notable and the 48h and 72h groups were both classified as a very incipient decay (ICDAS 1) but with lack of clinical differences amongst it. Nevertheless, using the laser speckle image, the ANN was still capable of achieving an accuracy o 57.26% in the worst case.

Silva et al, (2020), using an enamel erosion model, showed that the relative contrast of the group submitted to 24h of acid etch was 11.5(15)%. At the significance level $\alpha = 0.05$, there was a statistically significant difference between this group and the sound region ($p < 0.0001$), demonstrating that the analysis of the statistical maps of the laser speckle image of dental enamel is sensitive enough to detect changes subtle changes in the dental microstructure caused by the lesion induction process. Increasing the acid etching duration, there was an evolution in the relative contrast to 16.5(23)% and 20.8(20)%, respectively, for 48h and 72h, demonstrating a correlation between the induction process (etch duration) of a lesion similar to erosion and laser speckle imaging.[**Error! Bookmark not defined.**]

In this work, the increase in injury severity did not occur linearly with the duration of the acid etch. Table 2 shows that there is a good separation between sound data and data with 24h of acid etch, as well as between 24h and 48h, however, such a separation was not observed between 48h and 72h, which can be corroborated by Silva et al, (2020) .[**Error! Bookmark not defined.**].

The first time of the acid etch (24h) results in a very incipient lesion being commonly confused (even by trained professionals) with a sound tooth. Even observing the subtle differences between sound and decayed enamel under these conditions, in most samples, such a lesion does not have the minimum characteristics to be classified as ICDAS 1. It is important to emphasize that this lesion does not have clinical implications, meaning it does not yet require any type of intervention by the health professional. However, even under these conditions, the ANN can distinguish 24h lesion from its neighbors (sound or 48h) with an accuracy greater than 74% in both cases.

Lesions obtained after 48h and 72h of acid etch are more severe but still classified as ICDAS 1 (least lesion on the ICDAS scale), requiring a minimally invasive approach by the dentist. In these cases, the network was able to distinguish sound teeth from decayed teeth properly but found it difficult to distinguish 48h from 72h.

When using 4 injury classifications, the accuracy was between 62% and 64% in all cases, regardless of the information used in the network input (raw data, statistical characteristics, PCA, or a combination of these). The similarity in the severity of the injuries contributed to the decrease in accuracy and not even the analysis of the statistical attributes was able to increase the percentage of correct answers. However, in many cases, even specialists find it difficult to distinguish between the lesions. In the confusion matrices, it was noted that, when the ANN was required to classify all degrees of severity simultaneously, there was a lot of error in the classification of the 24-hour lesion, which is generally classified as sound. On the other hand, this phenomenon was not observed when only the SD and 24h groups were classified, where the classification obtained an accuracy of 86.5%.

It is important to highlight that the previous works were limited to detecting the presence or absence of the lesion, however, in this work, for the first time, the quantification of the degree of severity of the lesion was carried out using ANN, since the different times of acid attack induce lesions of different stages.

All techniques for extracting information from coherent light scattering patterns are based on Statistical Theory, however, the lack of increased accuracy when using the various statistical descriptors associated with the image shows that it is possible to extract information directly from the light scattering pattern without the need for a statistical treatment of the image.

The analysis using PCA showed that it is possible to reduce the dimension of the problem (and consequently the computational cost for training the network) without loss of information, however, there was no increase in accuracy.

5. CONCLUSIONS

This study demonstrates, for the first time to our knowledge, that it is possible to quantify the progression of the incipient caries-like lesion (white spot) by enhancing the contrast between sound and decayed dental tissue using laser speckle analysis, and machine learning techniques.

The proposed technique demonstrated, for the first time, the ability to quantify the severity of incipient lesions, however, it has difficulty in distinguishing lesions with similar severity (48h and 72h). This difficulty is similar to that encountered by dentists in clinical practice, where many cannot differentiate between lesions. It is important to emphasize that not even the most severe injury surpassed 1 on the ICDAS scale, that is, this work demonstrates that the proposed technique was able to quantify injuries that still do not require any type of intervention by the health professional.

It was also demonstrated that, using intelligent classifiers, it is possible to extract information directly from the raw laser speckle data, without the need for a statistical data treatment as preconized by the literature.

6. ACKNOWLEDGMENTS

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