Analysis of Relationship between Gate Drive Condition and Detection Sensitivity of Bond Wire Lift-Off in IGBT Modules using Convolutional Neural Networks (CNNs)

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***Abstract*— Bond wire lift-off is a major failure mode in IGBT modules, and monitoring the gate-emitter voltage (V_{ge}) waveform provides an effective indicator for detection. This study applies convolutional neural networks (CNNs) to evaluate waveform sensitivity and its impact on classification accuracy under various gate drive conditions. Here, sensitivity refers to the ability to detect fault-related waveform features, while accuracy represents the overall correctness of the classification. Waveform segments analysis reveals that specific regions contribute strongly to detection, while a performance map clarifies the learning progress between training and testing accuracy. The results show that two-step vector control (2-sVC) greatly improves sensitivity, and CNNs can still recognize subtle waveform changes under conventional control. These findings demonstrate CNN's capability for robust and generalizable health monitoring of power modules.**

Keywords*— *Bond wire lift-off, Convolutional neural networks (CNNs), Gate waveform sensitivity, IGBT modules.

I. INTRODUCTION

The reliability of power semiconductor devices is a critical issue for power electronic applications [1] such as renewable energy converters, electric vehicles, and motor drives. Among the various failure mechanisms of insulated gate bipolar transistor (IGBT) modules, bond wire lift-off has been identified as one of the dominant degradation modes during power cycling stress. The bond wire lift-off phenomenon increases the parasitic emitter inductance (L_{EE})[2][3][4], which affects the gate-emitter voltage (V_{ge}) waveform during the switching process[5]. As a result, the gate waveform has been widely studied as a promising indicator for online health monitoring of IGBT modules [6][7].

Previous research has proposed several methods to detect bond wire lift-off from gate signals, including the analysis of the Miller plateau duration, gate current transients, and voltage overshoot [8][9][10]. More recently, our studies demonstrated the digital gate control (DGC) technique. Particularly, the two-step vector control (2-sVC) can enhance the sensitivity of bond wire lift-off detection by enhancing the waveform features such as the voltage spike amplitude (ΔV_{ge}) and timing shift (Δt_{wire}) [11][12]. Following this work, it also applied artificial intelligence (AI) methods that use a convolutional neural network (CNN) trained on gate voltage waveforms to classify the level of bond wire degradation with high accuracy [13]. The results showed that CNN-based estimation achieved superior detection performance compared with conventional approaches, particularly when using waveforms generated by 2-sVC switching [14].

While those studies confirmed that CNN can reliably detect and classify bond wire lift-off. However, the key research gap remains understanding the sensitivity behavior of waveform features when analyzed by CNN. In other words, although CNN achieves high classification accuracy, it is still unclear which physical waveform characteristics contribute most to predictions and lacks consideration of how the behavior of sensitivity of these features is reflected in the CNN learning process. This study focuses on analyzing the sensitivity of waveform features in depth. Clarifying this relationship is essential not only for optimizing AI-based monitoring systems but also for guiding the design of gate driver control strategies and test procedures for robust condition monitoring.

Therefore, this paper presents a sensitivity analysis of bond wire lift-off in IGBT modules from gate waveform patterns using CNNs. The study investigates the correlation between physically measurable sensitivity indicators (ΔV_{ge}, Δt_{wire}, dI_e/dt) and AI-derived sensitivity features identified by CNN learning. Furthermore, the robustness of CNN classification is evaluated under various operating conditions and waveform segments to reveal how sensitivity influences learning performance. This approach provides a deeper understanding of how waveform sensitivity impacts AI-based bond wire lift-off detection and offers design insights for developing more reliable health monitoring methods in practical applications.

II. METHODOLOGY

A. Experimental Setup

The experimental evaluation was conducted using a double-pulse test circuit to characterize the switching behavior of IGBT modules. The circuit was designed with a DC supply, load inductor, and capacitor, as shown in Fig. 1. The test condition current was 100 A, and the DC voltage was 300 V at room temperature. Gate voltage waveforms (V_{ge}) were measured using a high-bandwidth oscilloscope, with sampling rates sufficient to capture transient switching phenomena. Bond wire lift-off was emulated by physically removing wires in a cutting step to create 4 degradation levels (levels 1-4, including no damage, light, medium, heavy) [11][14]. The V_{ge} waveform collection process, where the digital gate driver generates the control signals using a double-pulse testing setup. Then the PXI-oscilloscope (LabVIEW product) records the corresponding V_{ge} waveforms [14]. These captured signals are recorded as the input dataset for training in CNNs.

The sensitivity depends on the digital gate control (DGC) driver that was employed to manipulate switching characteristics (This experiment was conducted for the turn-off waveform). Two control strategies were compared: Conventional Vector Control N (CVC) and Two-Step Vector Control (2-sVC). CVC adjusts the gate current by varying a single control vector, while 2-sVC uses two sequential vectors (N_{1st}, N_{2nd}) with defined time durations (T_{1st}, T_{2nd}). The 2-sVC approach enhances waveform sensitivity by suppressing collector voltage overshoot and amplifying the spike features associated with bond wire lift-off [11][12][14].

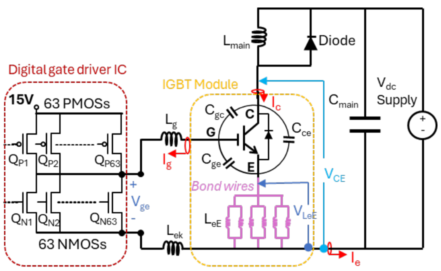

Fig. 1 Double pulse testing and IGBT equivalent circuit

Fig. 2 illustrates the V_{ge} waveforms under CVC with different vector numbers (N = 63, 30, 8, 4). As the N decreases with the switching speed changes, the number of sampling points per waveform varies. Fig. 3 presents the V_{ge} waveforms under 2-sVC, which are combinations of (N_{1st}, N_{2nd}). The results highlight that 2-sVC can enhance voltage amplitude compared to CVC [11][12].

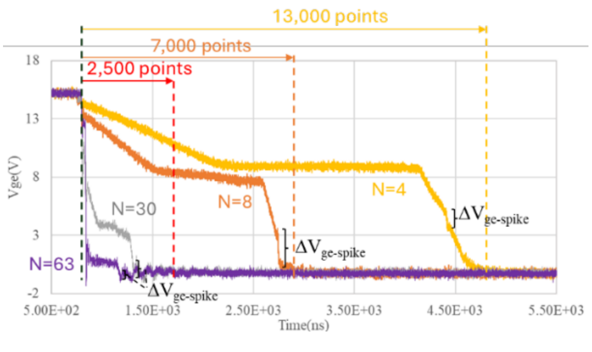

Fig. 2 V_{ge} waveforms under conventional vector control (CVC)

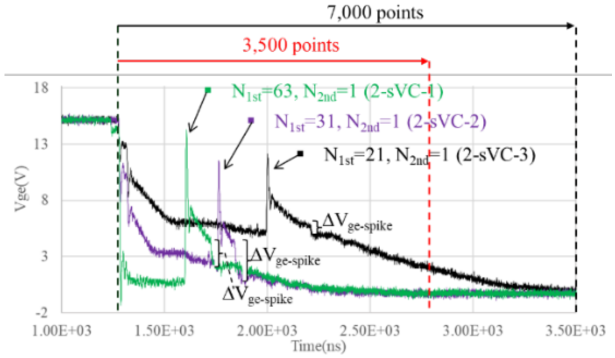

Fig. 3 V_{ge} waveforms under two-step vector control (2-sVC)

B. CNN Structure and Evaluation Metrics

The collected V_{ge} waveforms, prepared as input datasets for a CNN model, include 2,500 datasets for each bond wire lift-off condition (1-4), a total of 10,000 waveforms per control condition. The CNN architecture, shown Fig. 4 consisted of reshaping layers, 1D convolutional layers with ReLU activation, pooling layers for dimensionality reduction, and dense layers for final classification. The input waveforms were tested both with and without normalization before entering the network, in order to evaluate the effect of preprocessing on learning performance. The last layer used a SoftMax activation to classify the waveforms into four bond wire conditions (no damage, light, medium, and heavy). The dataset splitting process, where the collected 10,000 waveforms for each control condition were divided into 80% training data and 20% testing data. This splitting ensured sufficient samples for training while reserving independent data for testing CNN generalization and accuracy.

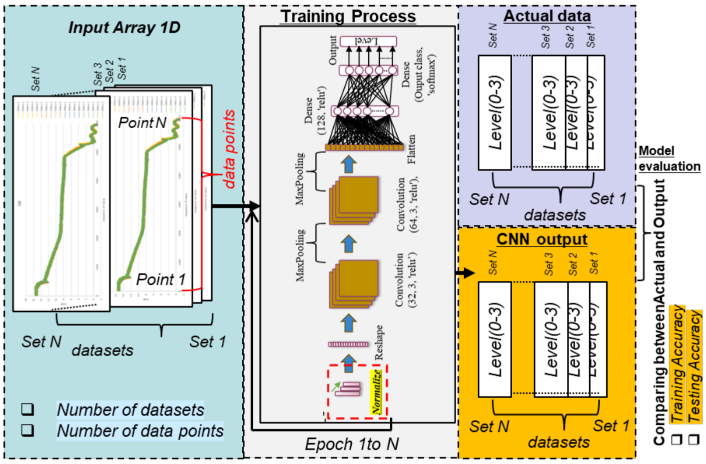

Fig. 4 CNN model training and evaluation process

C. Training and testing curve analysis

To evaluate the learning performance of the CNN, the training and testing accuracy curves were analyzed. The accuracy progression was monitored epoch by epoch, where rapid convergence and stable testing accuracy indicate strong generalization capability. Conversely, slow convergence or large fluctuations between the training and testing curves suggest potential overfitting or insufficient feature extraction. This provides a straightforward method to assess the robustness of the CNN model.

Fig. 4 illustrates the CNN training and evaluation process, where waveform datasets are divided into training and testing sets. CNN process is repeatedly trained across epochs, and its outputs are compared with actual labels to calculate accuracy. Furthermore, the fitting behavior of the model can be interpreted by examining the data distribution, as shown in Fig. 5. When features overlap, the decision boundaries must be fitted to ambiguous (stack) regions, increasing the risk of overfitting or underfitting. In contrast, when features are well separated, the CNN achieves fitting with clear margins for supporting stable training and reliable generalization. This conceptual framework provides the basis for understanding the subsequent analysis of waveform sensitivity.

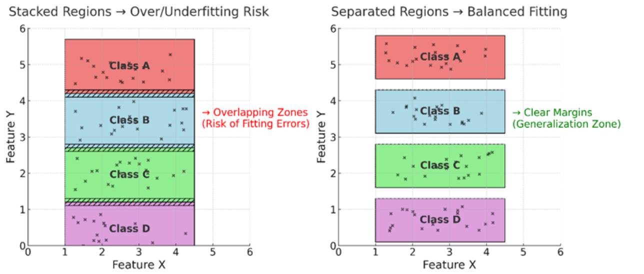

Fig. 5 Data classification distribution on model fitting behavior

Furthermore, the training and testing curves can be described using a performance map, as shown in Fig. 6. In this map, the horizontal axis represents training accuracy, and the vertical axis represents testing accuracy. To present different fitting behaviors to be visualized. Underfitting appears in the lower-left region, where both accuracies are low, while overfitting occurs in the lower-right region, where training accuracy is high, but testing accuracy remains low. The upper-left region corresponds to suspicious cases with unusually high testing accuracy despite low training accuracy. A balanced progression from poor to ideal fitting lies along the diagonal, with the top-right corner (100/100) representing the ideal state of strong generalization. This performance map provides an additional perspective beyond accuracy curves and complements the fitting behavior illustrated in Fig. 5, to assess data classification distribution.

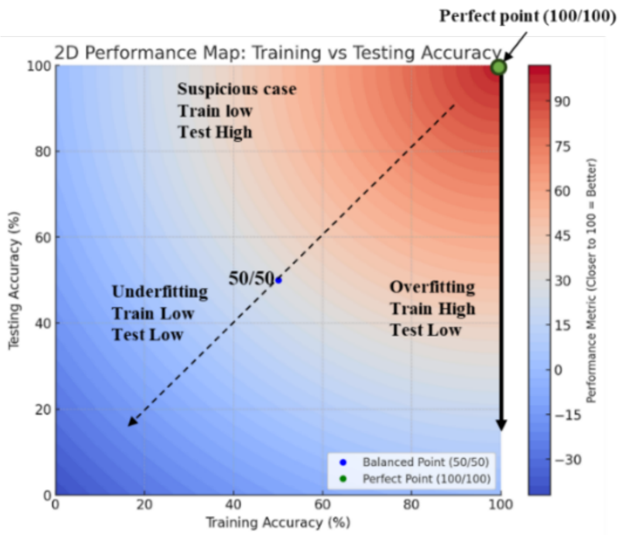

Fig. 6 CNN performance map training vs testing curve analysis

III. Results and Discussion

A. Effect of Digital Gate Control on Waveform Sensitivity

Fig. 7 presents the CNN classification accuracy across different control conditions, comparing normalized and non-normalized datasets as well as the effect of varying vector numbers. The result shows that normalized inputs maintain consistently higher accuracy than non-normalized inputs. Especially at higher vector numbers, where dynamic avalanche (DA) effects are significantly high accurate. It also illustrates that optimal vector settings, such as N = 63, 8, and 2-sVC conditions, accuracy is the best classification outcome due to clearer waveform sensitivity features. These observations confirm that waveforms with gate control conditions are critical to achieving stable and high classification accuracy. Therefore, normalization and vector number control together enhance the robustness and reliability of CNN-based sensitivity analysis.

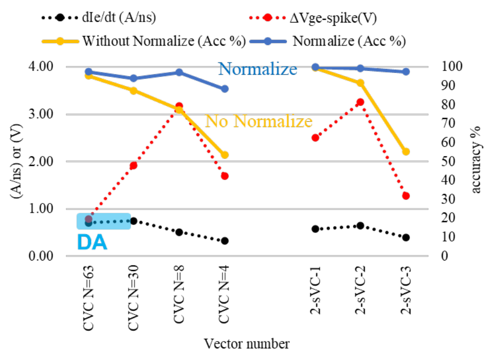

Fig. 7 CNN classification accuracy with and without normalization

However, it can be considered that in some cases the CNN still achieved high accuracy even without normalization. This outcome suggests that the waveform sensitivity was so clear a sensitivity margin under those specific conditions, CVC N=63 and 2-sVC-1, that the CNN could effectively distinguish bond wire lift-off levels without the normalization of preprocessing.

Fig. 8 presents accuracy improves with number of training data, but CVC requires large datasets due to weaker waveform sensitivity. In contrast, 2-sVC-1 achieves high accuracy with fewer datasets. Normalization further stabilizes performance, showing that optimized vector control and normalization reduce training data requirements for bond wire lift-off detection.

The relationship between gate drive conditions and bond wire lift-off detection is directly linked to the switching transient dynamics and parasitic elements in the IGBT module. Bond wire lift-off increases the effective emitter parasitic inductance, which modifies the current commutation behavior and alters the V_{ge} waveform, particularly the transient slope during switching. Under conventional vector control (CVC), these waveform variations remain relatively small, resulting in lower waveform sensitivity and requiring larger datasets for reliable CNN classification. In contrast, optimized gate drive conditions, such as two-step vector control (2-sVC), enhance the interaction between the current transient and the parasitic inductance, thereby amplifying the waveform differences caused by bond wire lift-off. This improved waveform sensitivity increases fault observability and enables more accurate and data-efficient CNN-based fault detection.

B. Waveform Segmentation and Sensitivity Analysis

An average of 10,000 waveforms for each control condition and bond wire lift-off levels (1-4), as in Fig. 9 . For CVC, the average waveform responses at different vector numbers (N = 63, 30, 8, 4) demonstrate the four bond wire lift-off levels. 2-sVC-1, the average waveform responses are more compact and emphasize region III, improving the classification of bond wire lift-off levels. The averaging value reveals consistent waveform differences that are crucial for CNN learning, and 2-sVC enhances the sensitive portions of the waveform compared to CVC.

The waveforms in Fig. 9 can be considered into three regions, including regions I, II, and III, to evaluate sensitivity more precisely. Region I corresponds to the initial transient where the gate discharge begins. Region II during the Miller plateau area. Region III represents the last part of the waveform, where $\Delta V_{ge\text{-}spike}$ occurs due to the emitter current fall, resulting in a voltage being induced.

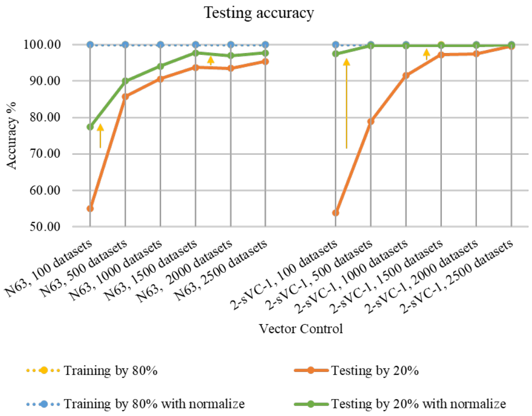

Fig. 8 CNN classification accuracy dependence on the number of datasets per condition for CVC N=63 and 2-sVC-1.

The Fig. 10 depicted accuracy varies when the waveform is segmented into regions I, II, and III (Parts 1–3, respectively), and "Full" represents the entire waveform. The observations show that 2-sVC-1 and CVC $N = 63$ achieve higher accuracy and more stable classification performance across all regions. The red-marked areas highlight region III, which indicates stronger performance under normalization rather than non-normalized cases. At the same time, the waveform analysis confirms that the majority of sensitivity is concentrated in region III. As a result, waveform includes an induced voltage spike (ΔV_{ge}) during I_e falling and provides the clearest sensitivity features. This demonstrates that normalization improves robustness sensitivity for CNN classification for bond wire lift-off levels.

The comparison between vector control conditions observed that regions I and II exhibit high sensitivity in conditions $N = 63$ and 2-sVC-1. Because $N = 63$ employed the large gate current (I_g) in these regions, which amplifies the waveform differences caused by bond wire lift-off. This strong current response enhances CNN's ability to extract meaningful features, leading to high classification accuracy even without normalization. In contrast, for other conditions, $N = 4$, 8, and 30, the gate current is smaller, resulting in weaker waveform variation and lower estimation accuracy. These observations confirm that regions I and II of 2-sVC-1 achieve the same behavior sensitivity characteristics as CVC at $N = 63$, owing to N_{1st} of 2-sVC-1 also being 63.

C. CNN Performance Score as an Indicator of Sensitivity

Fig. 11 shows the progression of CNN performance under different switching control modes. The upper plot illustrates the training process as the number of epochs increases. For $N = 4$, the learning progress is slow, and accuracy fluctuates significantly, which implies unstable learning and weak generalization. The case of $N = 30$ exhibits smoother improvement and better consistency between training and testing accuracy, although the overall accuracy remains moderate. In contrast, $N = 8$ and 63 begin with faster learning progress and converge steadily, with the testing curve closely following the training curve, which suggests reliable generalization. The 2-sVC-1 condition demonstrates the most efficient trajectory, where both training and testing accuracy increase rapidly and stabilize at a high level that reflects early convergence and strong robustness.

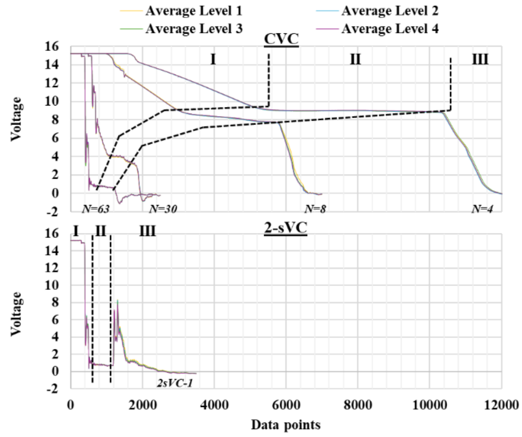

Fig. 9 Averaged V_{ge} waveforms (10,000 samples) under CVC and 2-sVC conditions

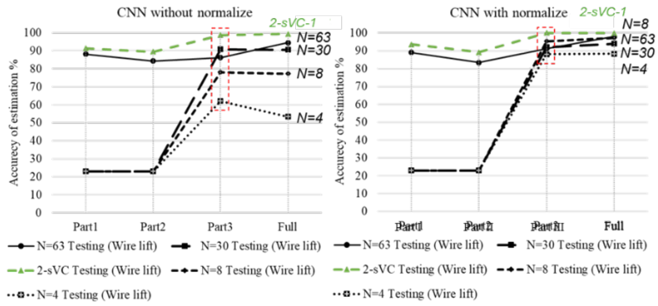

Fig. 10 CNN classification accuracy with waveform regions for CVC N=63 and 2-sVC-1

The bottom Fig. 11 zoomed-in plot highlights the clustering of results. The distribution for $N = 4$ remains scattered, while $N = 30$ forms a moderate cluster around the 90–95% range. For $N = 8$ and 63, the results converge into tighter clusters around 95% testing accuracy that reflect stable performance with reduced variance. The 2-sVC-1 condition achieves the most compact grouping close to 100%, confirming nearly perfect fitting. Importantly, regions I and II can be identified for both $N = 63$ and 2-sVC-1, particularly regions III correspond to high-sensitivity conditions, since the digital gate control enhances the gate voltage waveform caused by bond wire lift-off. As reported in previous works, this sensitivity is expressed by larger Δt_{wire} and $\Delta V_{ge-spike}$ [11][12]. As discussed, the choice of vector numbers strongly influences the stability of learning and the generalization capability of the model. CVC $N = 4$ leads to unstable behavior with large fluctuations, while vectors $N = 30$ provide more consistent improvement but remain limited in accuracy. Larger vectors $N = 8$, 63 enhance convergence with strong generalization, whereas the 2-sVC-1 condition achieves the best outcome with compact clustering near 100% accuracy and almost perfect fitting. These observations are summarized in TABLE I, which categorizes the CNN performance according to training behavior and generalization capability. However, this experiment was performed only under fixed operating conditions: a DC voltage of 300 V, a test current of

100 A, and room temperature. Therefore, further investigation is required to evaluate the model performance under diverse voltage, current, and thermal environments.

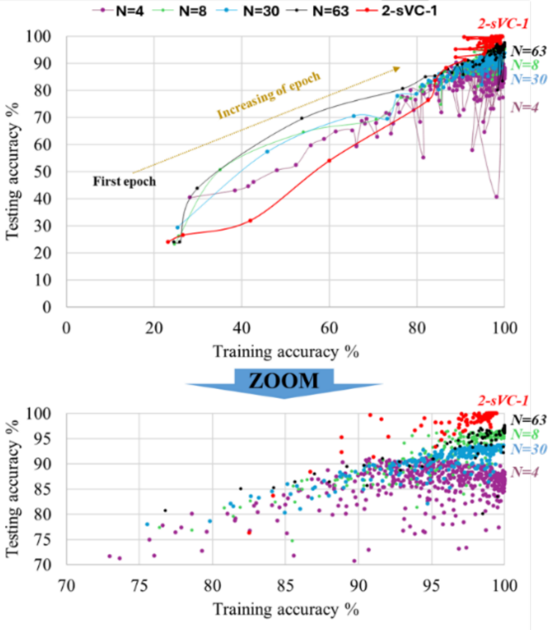

Fig. 11 CNN performance score map

TABLE I. THE DESCRIPTION OF CNN PERFORMANCE

Condition	Behavior	Generalization
$N = 4$	High variance, unstable learning	Underfitting or Overfitting
$N = 30$	Balanced performance with moderate stability	Stable generalization
$N = 8, 63$	Strong convergence with tighter clustering	High sensitivity, good generalization
2-sVC-1	Rapid convergence, compact distribution near 100%	Closely approaches perfect fitting and ideal generalization

IV. CONCLUSION

This work presented a detailed sensitivity analysis of bond wire lift-off detection in IGBT modules using CNNs trained on gate voltage waveforms. The results demonstrated that CNN performance strongly reflects the sensitivity of the control waveform condition. Normalization improved accuracy and stability across all switching conditions, while optimized vector control (2-sVC-1) provided the clearest sensitivity features, enabling near-perfect generalization. The waveform segmentation analysis confirmed that region III contributes the most to sensitivity, matching CNN learning with physical indicators such as $\Delta V_{ge\text{-}spike}$ and Δt_{wire}. Importantly, the CNN was able to detect bond wire lift-off even under very weak sensitivity conditions (CVC N = 63), region I and II, achieving results comparable to 2-sVC-1 when sufficient data and preprocessing were applied. These findings highlight the combined benefits of optimized gate control strategies and AI-based analysis, enabling robust and generalizable health monitoring for power electronic modules.

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