Leveraging Voice for Early Detection of Chronic Kidney Disease: Enabling Continuous Monitoring in Remote Healthcare

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***Abstract*—Chronic Kidney Disease (CKD) represents a globally prevalent condition characterized by the gradual loss of renal function over time. The covert progression of CKD accentuates the necessity for regular and continuous inspection. Conventional diagnostic methods for CKD, including blood and urine analyses to estimate the Glomerular Filtration Rate (GFR) and to measure the urine Albumin-Creatinine Ratio (uACR), while effective, are invasive and often fail to facilitate early detection due to the asymptomatic progression of CKD in its initial stages. To tackle these limitations, we propose a novel, non-invasive diagnostic technique to enhance the early detection and management of CKD. This technique utilizes the patients' voice features, caused by respiratory muscle weakness and vocal chord swelling in patients with CKD, as an auxiliary indicator, leveraging machine learning algorithms to identify subtle changes in voice patterns that may correlate with CKD progression. Our method demonstrated a diagnostic accuracy of 0.86, quantified by the F1 score, and showed promising potential as a supplementary diagnostic tool. Implementing this technique paves the way for its integration into telemedicine platforms, offering a promising avenue for remote monitoring and managing CKD patients. This breakthrough advances our understanding and capability in the early diagnosis of CKD. It expands the potential for remote healthcare delivery, ensuring timely intervention and improving patient outcomes in managing kidney conditions.**

***Keywords*—chronic kidney disease; automatic classification; machine learning; explainable artificial intelligence.**

I. Introduction

Kidney disease is a decrease in the Glomerular Filtration Rate (GFR), which refers to the degree of waste removal in the kidney, or when the signs of structural or functional decrease of the kidney are detected by blood, urine, radiation, or other kidney pathology tests [5]. It affects approximately 8% to 16% of the world's population and is the leading cause of death worldwide [19]. Among them, a case where this decrease in kidney function lasts for more than three months is called Chronic Kidney Disease (CKD). This status can cause not only kidney failure but also some other adverse outcomes such as cardiovascular disease and ultimately cause the need for dialysis or renal replacement therapy [16].

The clinical research underscores the importance of prompt identification and therapeutic intervention for stage 3 CKD to avert additional deterioration of renal function and the advancement to renal failure [14]. The study presents compelling evidence that early detection, accurate staging, and suitable management of CKD can mitigate these negative consequences and diminish the overall impact of the disease. However, one of the key challenges in the early detection of CKD is its silent progression. In its early stages, symptoms are often absent [17], and traditional diagnostic methods such as blood and urine tests require regular medical check-ups, which hinders early detection and continuous monitoring. Accordingly, there is a growing demand for auxiliary indicators that can diagnose CKD non-invasive and iteratively.

To find them, we focused on the fact that CKD impacts multiple body systems, such as the cardiovascular, nervous, musculoskeletal, immune, endocrine, metabolic, and respiratory systems. Among them, the close functional relationship between the lungs and kidneys in maintaining the body's acid-base balance means that renal changes can significantly affect respiratory health. This link is evident in CKD patients, who often exhibit reduced respiratory muscle strength and endurance and, in advanced stages, may experience decreased lung function and vocal cord edema due to uremic accumulation, acid-base imbalance, and volume overload [7].

From these respiratory changes in the patient's voice, we propose that the voice can be an auxiliary indicator and demonstrate its potential through some experiments. We collected data from patients with a wide range of kidney health statuses, from stage 1 CKD (CKD 1) to stage 5 (CKD 5), alongside a healthy control group. We crafted data for CKD prediction by extracting extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) features from collected voices and combine them with simple demographic data and biometric data from patients, such as age, sex, Body Mass Index (BMI), etc. We train the model with an internal training set and validate it with an external validation set. Consequently, we developed an automated CKD diagnostic system demonstrating an F1 score of 0.86.

This approach could serve as non-invasive and cost-effective markers for the early detection and monitoring of CKD and revolutionize early diagnosis and severity prediction, offering a readily accessible and repeatable tool for tracking disease progression. This could significantly improve patient outcomes by enabling timely interventions while also reducing the reliance on traditional, invasive testing methods.

Our study has opened up new research possibilities by demonstrating the potential of speech-based diagnosis in CKD management, where the interest and importance of remote health monitoring are increasing. The high accuracy of our system in severity detection and simple inspection of CKD

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through voice analysis can lead to significant improvements in the field. This introduces the feasibility of non-invasive and cost-effective methods for screening severity and presents scenarios for using such techniques in a real-world setting. This development opens new avenues for remote patient monitoring, providing a more accessible and less burdensome alternative to conventional diagnostic methods, and has great potential for improving patient care for CKD and potentially other chronic diseases.

The structure of this paper is organized as follows: Section 2, *Preliminaries* provides a detailed description of the dataset, preprocessing steps, and evaluation metrics used in our study. Section 3, *Methods* elaborates on the methodologies employed for feature extraction and classification, along with the explainable Artificial Intelligence (AI) techniques applied. Section 4, *Results* presents a comprehensive analysis of the experimental results. Finally, Section 5, *Conclusion and Future work* concludes the paper with a summary of findings and discusses potential avenues for future research.

II. PRELIMINARIES

A. Dataset Description

The dataset utilized in this research consists of health information and audio recordings collected under informed consent from patients at Seoul National University Bundang Hospital and Sacred Heart Dongtan Hospital, both highly esteemed institutions in Korea. The data collection targeted individuals presenting with kidney disease, during which each participant recorded six sentences. This set of sentences, including a self-introduction, was carefully developed in collaboration with the Department of Korean Language and Literature at Seoul National University. The design of these sentences aimed to capture the Korean voice's unique characteristics comprehensively.

In this research, 538 individuals aged 20 years and older were included in cohorts. We compiled a comprehensive dataset that included 887 records of hospital visits, including initial consultations and subsequent follow-up appointments. The follow-ups were scheduled quarterly. For analytical purposes, each record of hospital visitation was considered a separate observation.

The demographic breakdown of the cohort is as follows: 52 individuals were identified as not suffering from CKD, while the remaining participants were diagnosed with CKD at various stages of its progression. Specifically, the distribution was 77 individuals at stage 1, 135 at stage 2, 178 at stage 3, 75 at stage 4, and 20 at stage 5 of CKD. The age distribution of the patient cohort predominantly spans from 50 to 80 years, exhibiting a slightly right-skewed normal distribution with a central tendency around the 60s.

The quantitative analysis of hospital visit records yielded the following results: 70 records were categorized as healthy, 104 were identified as Stage 1, 205 as Stage 2, 339 as Stage 3, 141 as Stage 4, and 28 as Stage 5 CKD. Consequently, the analysis showed a ratio of non-critical (comprising normal and Stage 1 and 2 conditions) to critical (encompassing Stages 3 to 5) conditions as 4:6, based on the data derived from hospital visits.

TABLE I
DATASET DESCRIPTION WITH MERGED CELLS.

Stages	# of patients	# of visits	Severity
CKD 0	52	70	Non-critical
CKD 1	77	104	
CKD 2	135	205	
CKD 3	178	339	Critical
CKD 4	75	141	
CKD 5	20	28	

Before its inclusion in our research, the dataset underwent a rigorous de-identification process, ensuring the removal of personal identifiers, such as patients' names and identification numbers. This step was critical in preserving patient confidentiality and adhering to privacy standards. Furthermore, the dataset received approval for international sharing from the Institutional Review Board (IRB), affirming its compliance with ethical standards and regulations for human subjects research. This careful preparation and ethical oversight underscore the dataset's suitability for our study, providing a foundation for reliable and respectful research into kidney disease diagnosis through voice analysis.

B. Preprocessing Details

We separated the record files into sentence units and suppressed noise to minimize external noise intervention. The number of channels and sampling rate were also converted to Mono and 16 kHz, respectively, to exclude intervention due to differences in recording equipment and software. After that, the 88-dimensional features were extracted from each record, and the duration of the utterance was also calculated.

For patient health data, categorical features were encoded. For males, it was encoded as zero and for females as one. For medical history, such as hypertension, diabetes, and so on, it was encoded as one if the patient had the disease and zero if not.

Since age is a critical feature impacting the diagnosis severity, highlighted by its prominent Shapley Additive exPlanations (SHAP) values in our analysis, we categorized the participants into two cohorts based on the median age threshold of 65. We carried out distinct experiments for each group.

Labeling for critical conditions was conducted based on the expertise of a nephrologist to differentiate between insignificant and vital stages of CKD. Patients categorized in stages 0 (healthy), 1, and 2 were deemed non-critical conditions, whereas those in stages 3, 4, and 5 were identified as critical. The classification of each stage was determined by the estimated Glomerular Filtration Rate (eGFR), along with the presence or absence of proteinuria and hematuria. Specifically, stage 0 is characterized by an eGFR greater than 90 $mL/min/1.73m^2$, without proteinuria or hematuria. Stage 1 patients exhibit an eGFR exceeding 90 $mL/min/1.73m^2$,

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in conjunction with proteinuria or hematuria. Stage 2 encompasses individuals with an eGFR ranging from 60 to 90 $mL/min/1.73m^2$, accompanied by proteinuria or hematuria. Stages 3, 4, and 5 are delineated for eGFR levels less than 60 $mL/min/1.73m^2$, with specific thresholds set at greater than 30 and less than 60, 15 to less than 30, and less than 15 $mL/min/1.73m^2$, respectively.

C. Evaluation Metrics

In this study, we employed precision, recall, F1-score, and Area Under ROC Curve (AUROC) as metrics to evaluate the performance of our model in diagnosing critical stages of disease. Precision is the proportion of patients correctly identified as critical out of all patients the model classified as such. Recall measures the proportion of actual critical patients that the model correctly identifies. Given our goal to facilitate rapid and accurate disease severity identification outside hospital settings—enabling patients with suspected severe conditions to seek hospital care for comprehensive diagnosis and treatment promptly—recall was prioritized as a key metric. To comprehensively assess our model's performance, we also considered the F1 score and AUROC as supplementary metrics, particularly useful in addressing potential data imbalances. The F1 score, representing the harmonic mean of precision and recall, evaluates the model's accuracy in predicting the critical class and its effectiveness in identifying all actual critical cases. Meanwhile, AUROC assesses the model's overall capacity to distinguish between critical and non-critical conditions, offering insights into its performance across varied dataset distributions. The Receiver Operating Characteristics (ROC) curve, in particular, plots the true positive rate against the false positive rate, providing a visual representation of the model's performance. This multifaceted evaluation strategy ensures a balanced understanding of the model's diagnostic capabilities, emphasizing the importance of early and accurate disease detection.

III. Methods

A. eGeMAPS

The extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) [8] is a feature set used in various voice research, including speech recognition and disease classification. It contains 88 parameters, including additional descriptors, such as frequencies (bandwidth, Mel-Frequency Cepstral Coefficient (MFCC) 1–4, spectral flux of F1, F2, and F3), energy and amplitude (shimmer, volume of sound, Harmonic to Noise Ratio (HNR)), spectrum (relative energies of alpha ratio, F2, and F3, H1–H2, H1–A3), time (ratio of cloudless peak, average length and standard deviation of meteoric regions, number of continuous meteoric regions per second). In this study, voice features were extracted using these eGeMAPS, and their validity was verified through experiments. This can also be confirmed from the result that the accuracy is improved when eGeMAPS features are used for disease classification using a linear kernel support vector machine and an ensemble classifier [13].

B. Machine Learning Classifier

In this study, we address the challenge of severity classification using high-dimensional, small-scale datasets, including categorical variables. Our approach leverages advanced machine learning classifiers, specifically the Support Vector Classifier (SVC) [2] and eXtreme Gradient Boosting (XGBoost) [9]. The SVC, a specialized form of the Support Vector Machine (SVM), effectively delineates decision boundaries or hyperplanes in a multidimensional space, facilitating accurate data classification. Concurrently, XGBoost employs an ensemble strategy, enhancing predictive accuracy by amalgamating multiple weak predictors, predominantly decision trees, into a cohesive and potent predictive model. These methods were chosen due to their robust capacity to navigate the complexities inherent in limited-sized, high-dimensional datasets [12] [15].

C. Model Explainability

In this study, we utilized Partial Dependence Plots (PDPs) [3] and SHAP [10] values as methodologies to assess the significance and influence of distinct features on prediction outcomes. PDPs were instrumental in illustrating the global effect of selected features on disease classification by delineating how alterations in the values of these features within their observed ranges impact the model's average predictions. This analysis enabled identifying features with substantial predictive power, enhancing our understanding of the model's functionality.

Simultaneously, SHAP values offered a granular, personalized examination by quantifying the contribution of each feature to individual predictions. This nuanced approach was essential for highlighting the specific roles of certain features, such as age, BMI, and F1 frequency, in the classifier's decision-making processes.

The integration of PDP and SHAP analyses provided a comprehensive view of how features affect disease prediction, significantly improving the interpretability of the model. This dual-method analysis confirmed the model's utility in clinical applications and revealed critical insights vital for directing subsequent research initiatives.

IV. Results

A. Correlation between Severity and Voice features

Before initiating the comprehensive experimental phase, we conduct a preliminary analysis to ascertain the correlation between the variables of interest, namely Critical and eGeMAPS features. This involved examining the relationship between critical conceptualization as a binary categorical variable and voice features characterized as numerical variables to assess the significance of their association. To this end, the point-binary correlation coefficient (r_{pb}) [4] and the corresponding p-value were computed.

The formula for the point-biserial correlation coefficient is below where M_1 and M_0 are the mean values on the continuous variable for the two groups defined by the dichotomous variable, s_n is the standard deviation of the continuous variable, n_1 and n_0 are the number of observations in each group of the dichotomous variable, and n is the total number of observations.

$$r_{pb} = \frac{M_1 - M_0}{s_n}\sqrt{\frac{n_1 n_0}{n^2}} \quad (1)$$

The p-value threshold was established at 0.05, facilitating the isolation of instances exhibiting a p-value below this benchmark, thereby affirming the statistical significance of their association with the feature in question. This process identified 72 significant features. Followings are the foremost ten outcomes.

TABLE II
TOP-10 FEATURES CORRELATED WITH TARGET VARIABLE.

Rank	Feature	abs(r_{pb})	p-value
1	**Age**	0.372	0.00
2	**Hypertension**	0.294	0.00
3	**Diabetes**	0.282	0.00
4	**MeanUnvoicedSegmentLength**	0.196	0.00
5	**spectralFlux sma3 stddevNorm**	0.192	0.00
6	**MFCC3 sma3 amean**	0.166	0.00
7	**loudness sma3 stddevNorm**	0.165	0.00
8	**MFCC3V sma3nz amean**	0.162	0.00
9	**loudness sma3 percentile20.0**	0.158	0.00
10	**VoicedSegmentsPerSec**	0.157	0.00

Inspection of the table elucidates that voice-related features predominantly occupy the upper ranks of the absolute correlation metric, each marked by a p-value less than or equal to 0.05, underscoring their statistical significance.

The findings from these analyses substantiate a notable correlation between voice features and Critical, reinforcing our hypothesis's foundational premises.

B. Overall Performance Evaluations

We conducted a series of comparative experiments to investigate the effectiveness of vocal characteristics in the early diagnosis of CKD. Initially, we focused on well-established health indicators such as age, Hypertension (HTN), and Diabetes Mellitus (DM) due to their significant association with CKD, as indicated by high point-binary correlation coefficients. The research has highlighted the independent correlation of factors like older age, increased systolic blood pressure, the prevalence of Type 2 DM, and a longer duration of DM with CKD incidence [11]. Based on this understanding, these indicators could significantly aid in determining CKD severity. To test this, we conducted classification experiments leveraging these health indicators. Following this, we explored the potential of vocal features alone to differentiate CKD severity levels without incorporating additional health information. The results from these experiments suggested that severity classification is feasible using fundamental health indicators, and vocal features alone can achieve comparable results. Our final experiments combined health and vocal information to classify CKD severity. Here, we used two feature sets of health information. The set 'Health I' is the main feature set we used previously: age, HTN, and DM. The other set, 'Health II', includes the previous three, additional information such as sex and BMI that may affect the voice, and additional medical history information collected for the management of patients with CKD, including heart failure, cancer, cardiovascular disease, and cerebrovascular disease.

TABLE III
PERFORMANCE EVALUATION.

Feature Set	Model	Precision	Recall	F1	AUROC
Voice Only	SVC	0.719	0.68	0.698	0.73
Voice Only	XGBoost	0.757	0.731	0.706	0.76
Health I	SVC	0.74	0.686	0.71	0.73
Health I	XGBoost	0.795	0.754	0.743	0.84
Health I & Voice	SVC	0.854	0.777	0.814	0.88
Health I & Voice	XGBoost	**0.876**	0.816	0.826	0.90
Health II & Voice	SVC	0.835	0.83	0.811	0.91
Health II & Voice	XGBoost	**0.876**	**0.882**	**0.857**	**0.92**

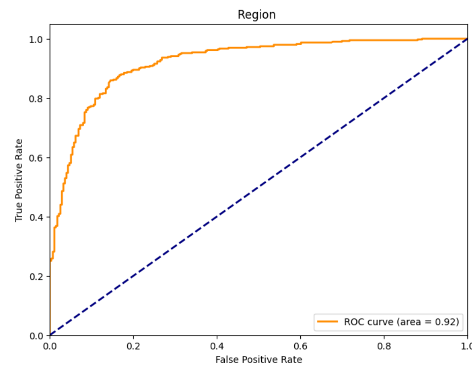

Fig. 1. ROC curve of *Using All*.

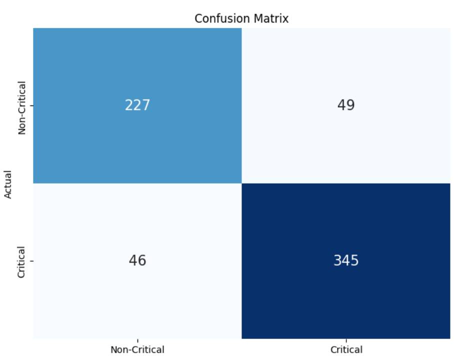

Fig. 2. Confusion Matrix of *Using All*.

The outcomes demonstrated superior classification performance across all metrics when integrating vocal features and all health information, affirming their positive impact on enhancing diagnostic accuracy. The comprehensive results are presented in Table 3, while Figure 1 and Figure 2 depict the ROC curve and the confusion matrix for the 'Using All' scenario, respectively.

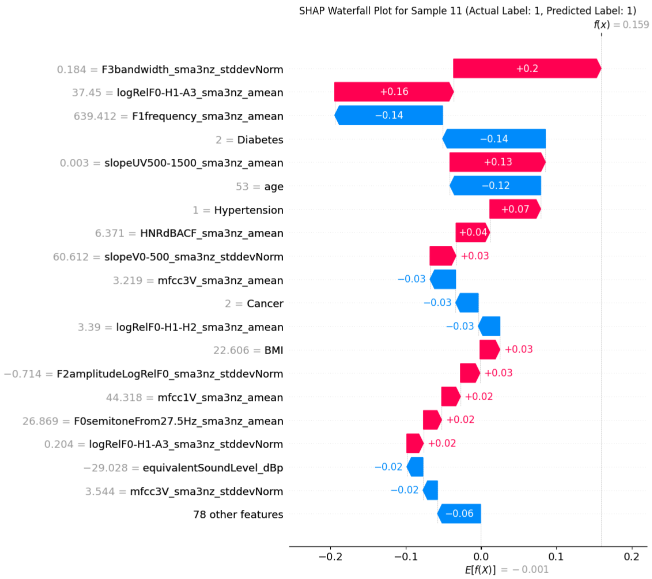

Fig. 3. SHAP Waterfall plot of Critical sample.

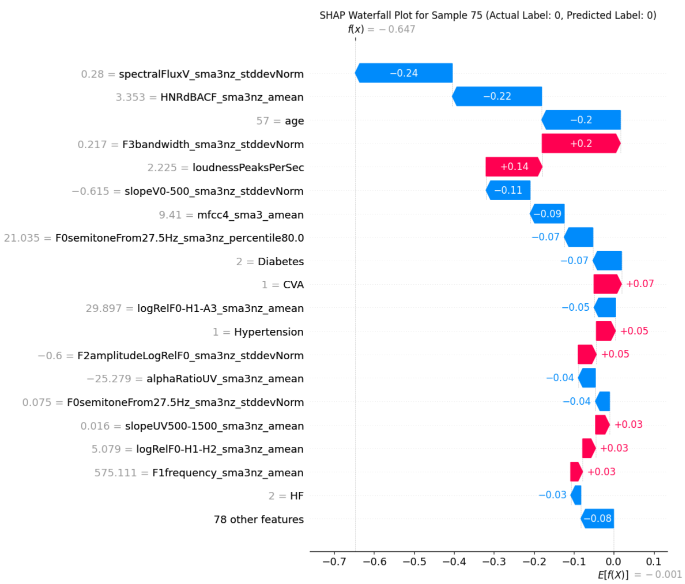

Fig. 4. SHAP Waterfall plot of Non-critical sample.

Figures 3 and 4 illustrate the significance of different features for individual samples, highlighting how certain features contribute to accurately predicting each sample's outcome.

For the first example, where the sample is labeled as 'Critical' (denoted by 1), factors such as age and a history of DM were initially misleading, suggesting a classification as 'Non-critical' (0). However, the presence of voice indicators allowed for the correct classification of this sample. Similarly, the second example, labeled as non-critical, demonstrated that voice features played a crucial role in ensuring the sample was classified accurately despite potential misdirection by some general health indicators. These observations underscore the potential of vocal attributes as reliable supplementary markers for diagnosis, particularly in instances where basic health information alone may lead to ambiguity.

C. Additional Experiments on Age-based separated groups

Age emerged as the most influential factor in our analysis, hinting at a potential overreliance on this variable. To explore this further, we conducted additional tests by dividing the subjects into two groups based on the median age of our patient cohort: those 65 and younger and those older than 65. Each group was then analyzed separately.

TABLE IV
AGE-BASED SEPARATED GROUPS.

Group	CKD 0	CKD 1	CKD 2	CKD 3	CKD 4	CKD 5
age<65	30	66	106	133	59	10
age≥65	21	19	76	197	81	17

The distribution indicates a tendency for the younger group (under 65) to lean towards less severe CKD stages (0, 1, and 2), whereas the older group (over 65) showed a skewed distribution to severe conditions. While the younger group exhibited a relatively balanced distribution across the severity spectrum, the older group displayed a pronounced disparity, with a distribution resembling a 3:7 ratio between non-critical and critical stages, respectively.

To address these disparities and reduce bias, we adjusted our model training approach to utilize Weighted Cross-Entropy (WCE) loss and evaluated the model performance using a Weighted F1-score. This methodology was chosen to lessen the influence of the observed imbalance in disease severity across different age groups. For clarity, we used only XGBoost, which performed relatively well in previous experiments.

TABLE V
PERFORMANCE EVALUATION ON AGE-BASED SEPARATED GROUPS.

Group	Precision	Recall	F1-Score	AUROC
all ages	0.876	0.882	0.857	0.92
under 65	0.849	0.827	0.852	0.92
over 65	0.909	0.879	0.853	0.92

The results show that the performance did not significantly decrease even when the group was separated based on age. Through this, the model did not depend too much on age and derived classification results by appropriately using the overall information.

V. CONCLUSION AND FUTURE WORK

In this study, we explored the use of patient voice features as biomarkers alongside traditional methods for diagnosing CKD. By employing machine learning techniques, we demonstrated the capability of voice features to classify the severity of CKD accurately. This approach opens new avenues for the continuous and remote monitoring of patients, particularly in severe cases where early detection and swift action are crucial.

Our findings reveal a clear correlation between specific voice features and the severity of CKD, highlighting the potential of vocal analysis in enhancing disease severity classification.

We aim to refine our classification methods by breaking down the severity of CKD into more detailed stages. This endeavor will likely require a more sophisticated experimental setup and the adoption of advanced machine learning technologies, including the potential use of deep learning models known for their robust capabilities. Additionally, we are considering applying voice signals to image-based models, such as multi-channel Convolutional Neural Networks (CNNs), through spectrogram-based voice imaging techniques for more precise voice analysis.

Nevertheless, our study faces the challenge of a limited dataset, a common issue in specialized research areas. To overcome this, we recognize the importance of expanding our dataset comprehensively. Implementing techniques to augment existing data could offer a viable solution to this limitation, enabling more extensive and in-depth research.

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