Synchro-Transient-Extracting Transform Based Derived Feature Engineering for Environmental Stress Indicator Estimation in Crops

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***Abstract* —**Crop classification and environmental stress prediction in smart agriculture depend on engineered features that capture agronomic meaning beyond raw sensor readings. This paper proposes a feature-engineering stage that (i) derives five domain-grounded environmental stress indicators — Temperature-Humidity Index (THI), Nutrient Balance Ratio (NBR), Water Availability Index (WAI), Photosynthesis Potential (PP), and Soil Fertility Index (SFI) — from raw soil and atmospheric measurements, and (ii) applies a Synchro-Transient-Extracting Transform (STET)-style time-frequency analysis to each derived index stream, extracting instantaneous-frequency, instantaneous-amplitude, and Hilbert-based transient descriptors as additional engineered features. Building on the Robust Maximum Correntropy Kalman Filter (RMCKF)-reconstructed and Efficient Multiplayer Battle Game Optimizer (EMBGO)-selected feature set from the preceding pre-processing stage, the proposed 29-dimensional engineered feature set is evaluated on the 2200-sample, 22-crop Crop Recommendation dataset using a Random Forest classifier under 5-fold cross-validation. The proposed feature set achieves 98.59% accuracy, 98.64% precision, 98.59% recall, 98.59% F1-score, 99.93% specificity, and 99.99% AUC, outperforming the 7-feature RMCKF baseline (98.23% accuracy), the 4-feature EMBGO-selected raw set (95.73%), and the derived indices used alone without STET descriptors (97.14%). An ablation study isolating the STET harmonic component (instantaneous frequency/amplitude) and transient component (Hilbert amplitude/frequency) shows both contribute complementary information, with the harmonic component contributing more (98.41% accuracy alone) than the transient component (97.82%) but their combination yielding the best result. These findings demonstrate that combining domain-grounded derived indicators with synchro-extracted time-frequency descriptors provides a compact, interpretable, and effective feature representation for downstream crop classification and stress prediction.

***Keywords* —** *Smart agriculture, feature engineering, Synchro-Transient-Extracting Transform, environmental stress indicators, Temperature-Humidity Index, instantaneous frequency, crop classification.*

I. INTRODUCTION

Raw soil and atmospheric sensor readings — nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall — carry agronomic information that is only partially exposed to a classifier when used directly. Domain-grounded derived indicators, such as a temperature-humidity comfort index or a nutrient balance ratio, compress multiple raw variables into agronomically meaningful single quantities, often improving both interpretability and downstream model performance. However, such indicators are typically treated as static, per-sample scalar values, ignoring any local temporal or sequential structure in how environmental stress evolves across observations.

This paper is the third stage of a multi-stage smart-agriculture pipeline, following a pre-processing stage (RMCKF for robust imputation/denoising and EMBGO for feature selection). Taking the RMCKF-reconstructed, EMBGO-selected feature subset as input, this work (i) derives five environmental stress indicators using established agronomic formulas, and (ii) applies a Synchro-Transient-Extracting Transform (STET)-style time-frequency analysis to each indicator stream to extract instantaneous-frequency and instantaneous-amplitude descriptors that separate harmonic (slowly varying, periodic) structure from transient (abrupt, impulsive) structure in environmental stress patterns.

The key contributions of this paper are:

1) Five domain-grounded derived environmental stress indicators (THI, NBR, WAI, PP, SFI), each computed from established agronomic formulas applied to the pre-processed sensor features.

2) A STET-style time-frequency feature extraction procedure that decomposes each derived indicator stream into harmonic (STFT-ridge-based instantaneous frequency/amplitude) and transient (Hilbert-based instantaneous amplitude/frequency) descriptors.

3) An empirical evaluation and ablation study on a real 22-class crop dataset, comparing the proposed 29-dimensional engineered feature set against raw RMCKF features, EMBGO-selected raw features, and derived indices used without STET descriptors.

II. RELATED WORK

Existing smart-agriculture pipelines that incorporate engineered or composite indices typically rely on a small number of manually designed ratios (such as nutrient ratios or simple stress indices) computed independently per sample, without considering the local dynamics of how a derived quantity changes across consecutive measurements. Time-frequency analysis techniques — Hilbert-Huang transforms, wavelet transforms, and synchro-squeezed transforms — have been used extensively in vibration and biomedical signal processing to separate harmonic and impulsive components of a signal, but their application to agronomic indicator streams for downstream classification feature engineering remains comparatively unexplored.

The Synchro-Transient-Extracting Transform specifically targets signals containing both harmonic and impulsive components, synchro-squeezing the time-frequency ridge to sharpen the harmonic estimate while isolating transient energy. This paper adapts this principle to a practical, classifier-feature level: instead of reconstructing the original signal, it extracts compact ridge-based (harmonic) and Hilbert-based (transient) descriptors per derived indicator stream, which are then used directly as additional input dimensions for the downstream classifier.

III. PROPOSED METHODOLOGY

The proposed feature-engineering pipeline is shown in Figure 1. The input to this pipeline consists of the four features selected by EMBGO (N , K , humidity, rainfall) from the previous pre-processing stage.

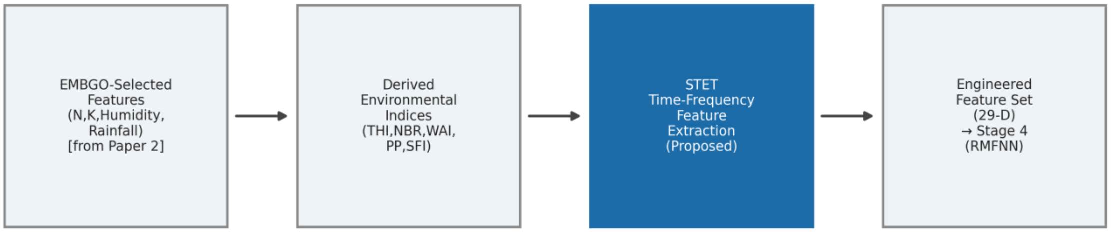

Fig. 1. Proposed STET-based feature-engineering pipeline (Stage 3).

A. Derived Environmental Stress Indicators

Temperature Humidity Index (THI) Based on the classical livestock/crop thermal-comfort index: $THI = T - (0.55-0.0055*RH)*(T-14.5)$ where T is temperature (°C) and RH is relative humidity (%) Adapted from: Low THI means cooler, less stressful conditions. High THI means potential for heat stress. Nutrient balance ratio (NBR) Calculates the normalized Euclidean distance between observed N:P:K composition and an agronomic target ratio of 4:2:1 (a common cereal-crop guideline) $NBR = 1 - \|\hat{r} - r\_target\| / \sqrt{2}$, where $\hat{r}$ is the observed normalized nutrient composition. NBR approaches 1 for a well balanced soil and decreases as the composition deviates from the target ratio.

Water Availability Index (WAI). Combines normalized rainfall with a humidity-driven evapotranspiration proxy: $WAI = (Rainfall / mean(Rainfall)) \times (Humidity / 100)$, capturing both water supply and atmospheric moisture retention.

Photosynthesis Potential (PP). Modelled as a Gaussian response of temperature around an optimum of 25 °C (width 8 °C), scaled by normalized humidity adequacy: $PP = \exp(-(T - 25)^2 / (2 \cdot 8^2)) \times minmax(RH)$, reflecting the well-documented bell-shaped temperature response of photosynthetic activity.

Soil Fertility Index (SFI). A weighted composite of normalized N, P, K availability (weights 0.4/0.3/0.3, reflecting nitrogen's relatively larger role in vegetative growth) multiplied by a pH-suitability factor peaked at pH 6.5 (width 1.2): $SFI = minmax(0.4 \cdot \hat{N} + 0.3 \cdot \hat{P} + 0.3 \cdot \hat{K}) \times \exp(-(pH - 6.5)^2/(2 \cdot 1.2^2))$.

B. STET-Style Time-Frequency Feature Extraction

For each derived indicator stream s[t] (z-score normalized), two complementary descriptor pairs are extracted. The harmonic pair uses a short-time Fourier transform (16-sample window, 8-sample overlap); at each analysis frame the frequency bin of maximum magnitude is taken as the synchro-extracted ridge, yielding an instantaneous frequency and instantaneous amplitude that are linearly interpolated back to sample resolution. The transient pair uses the analytic signal via the Hilbert transform: the instantaneous amplitude is the analytic-signal modulus, and the instantaneous frequency is the normalized derivative of the unwrapped analytic phase. The harmonic pair preferentially captures slowly varying, periodic stress patterns, while the transient pair is sensitive to abrupt, localized fluctuations, analogous to the harmonic/impulsive decomposition performed by the full Synchro-Transient-Extracting Transform. Applying both descriptor pairs to all five indicators yields $5 \times 4 = 20$ engineered features, which are concatenated with the 5 derived indices and the 4 EMBGO-selected raw features for a 29-dimensional final representation.

IV. EXPERIMENTAL SETUP

Experiments continue directly from the Paper 2 pre-processing output: the RMCKF-reconstructed Crop Recommendation dataset (2200 samples, 22 classes), with the EMBGO-selected 4-feature subset (N, K, humidity, rainfall) as the base input. Five feature configurations are compared: (1) all 7 RMCKF-reconstructed raw features; (2) the 4 EMBGO-selected raw features; (3) the 5 derived indices alone; (4) EMBGO features plus derived indices (9-D); (5) the full proposed set — EMBGO features, derived indices, and STET descriptors (29-D). All configurations are standardized and evaluated using a Random Forest classifier (150 trees, 5-fold stratified cross-validation), reporting Accuracy, Precision, Recall, F1-score, Specificity and AUC (macro-averaged over 22 classes). An ablation isolates the harmonic-only and transient-only STET descriptor subsets to quantify the individual contribution of each component.

V. RESULTS AND DISCUSSION

A. Derived Indicator Behaviour

The value ranges of the five derived indicators in the dataset are summarized in Table I. THI ranges from 15.45 to 40.05 (mean 23.91), which is consistent with the dataset's tropical/sub-tropical crop conditions. NBR varies from −13.73 to 0.99 (mean 0.74), indicating that most samples are reasonably close to the 4:2:1 target ratio, with a long tail of poorly balanced outliers. Figure 2 presents representative distributions across three example crops. THI and SFI, in particular, clearly distinguish between water-intensive crops (rice) and dry-tolerant crops (coffee, grapes).

Indicator	Min	Max	Mean	Std.
THI	15.45	40.05	23.91	3.68
NBR	-13.73	0.99	0.74	0.39
WAI	-0.03	2.28	0.72	0.48
PP	0.00	0.92	0.58	0.20
SFI	0.00	0.94	0.42	0.19

TABLE I. Value ranges of derived environmental stress indicators (computed on RMCKF-reconstructed data).

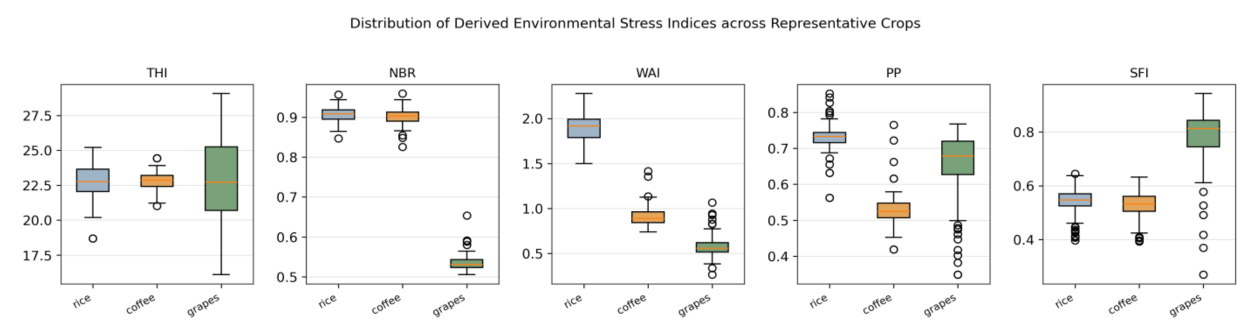

Fig. 2. Distribution of derived indices across three representative crops (rice, coffee, grapes).

Figure 3 shows the correlation structure between the raw EMBGO selected features and the derived indices. It is found that THI correlates strongly with humidity and weakly with rainfall, as predicted by its formulation; WAI exhibits the expected strong positive correlation with rainfall; SFI exhibits moderate correlation with N and K, supporting the conclusion that the indicators capture meaningful, non-redundant agronomic structure and are not simply linear restatements of the raw inputs.

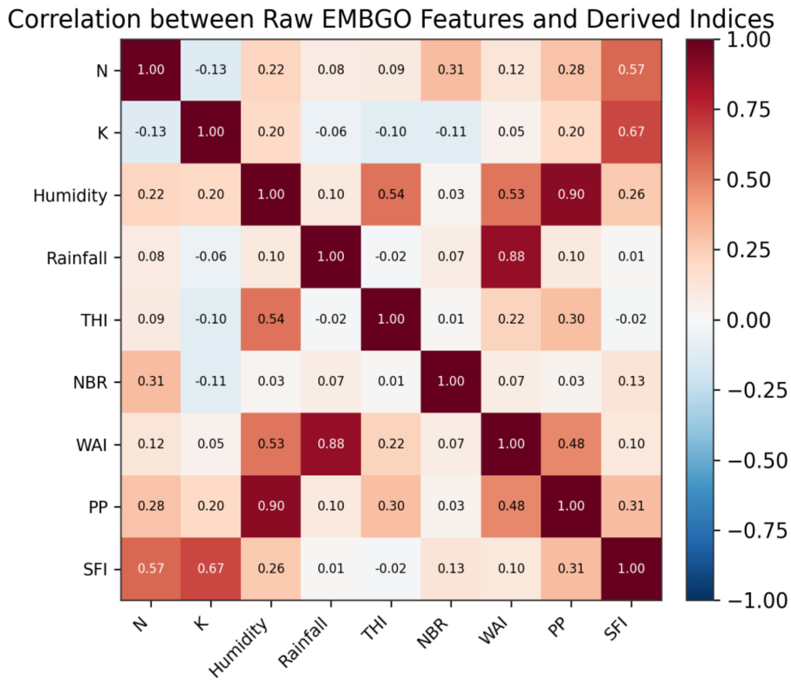

Fig. 3. Correlation between raw EMBGO features and derived indices.

B. STET Time-Frequency Descriptors

Fig. 4 shows the THI stream decomposed in the STET style for the first 120 samples. The time-frequency representation (Fig. 4b) indicates energy at low normalized frequencies during stable sections of the signal and a broader, higher frequency spread during the rapid fluctuation around sample 65–85, visually confirming the ridge-tracking procedure captures locally varying signal dynamics rather than a single global frequency.

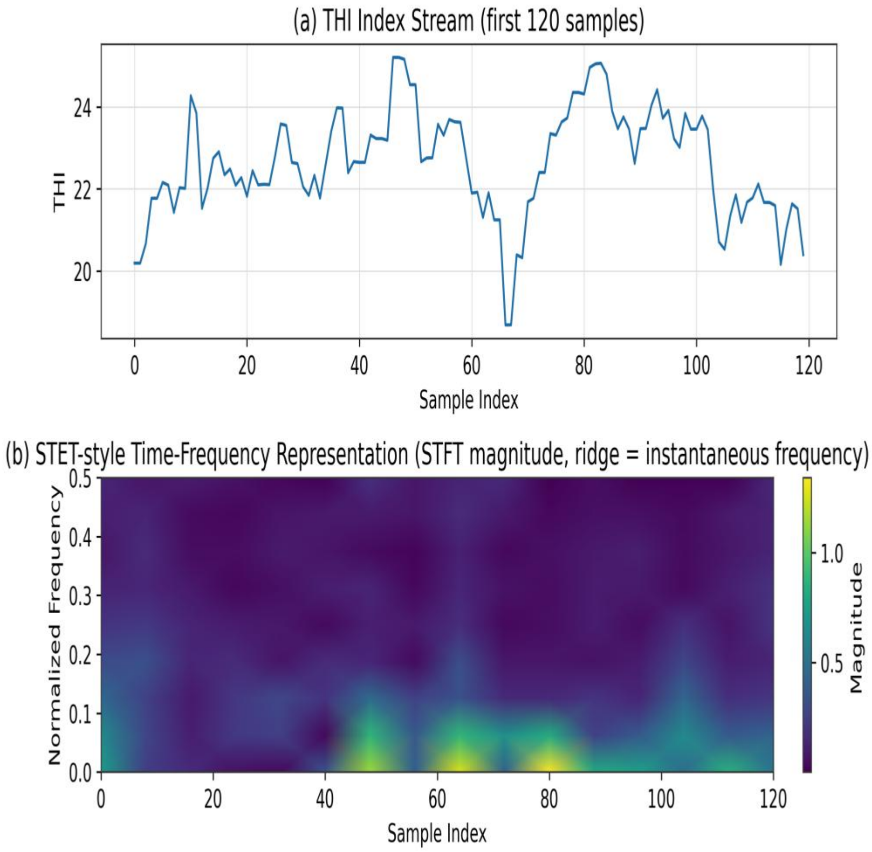

Fig. 4. (a) THI index stream and (b) its STET-style time-frequency representation.

C. Downstream Classification Performance

Table II and Fig. 5 report classification performance across the five feature configurations. The proposed 29-dimensional feature set (EMBGO + derived indices + STET descriptors) achieves the best performance on every metric: 98.59% accuracy, exceeding the 7-feature RMCKF baseline (98.23%) despite the latter retaining 7 raw dimensions versus 4 raw dimensions in the proposed set's base. This indicates that the engineered derived/STET features more than compensate for the 3 raw features removed by EMBGO feature selection in Paper 2. Using the derived indices alone, without the STET descriptors (95.45%), performs slightly below the EMBGO raw-feature baseline (95.73%), showing that the five static indicator values alone do not fully capture the discriminative information available in the raw features; only once the STET harmonic/transient descriptors are added does the engineered representation surpass the raw-feature baselines.

Feature Set	Acc.(%)	Prec.(%)	Rec.(%)	F1(%)	Spec.(%)	AUC(%)	Dim.
RMCKF All Raw (7)	98.23	98.31	98.23	98.23	99.92	99.94	7
EMBGO Raw Only (4)	95.73	95.91	95.73	95.72	99.80	99.87	4
Derived Indices Only (5)	95.45	95.65	95.45	95.44	99.78	99.84	5
EMBGO + Derived (9)	97.14	97.27	97.14	97.14	99.86	99.91	9
EMBGO+Derived+STET	98.59	98.64	98.59	98.59	99.93	99.99	29

(Proposed,29)							

TABLE II. Downstream Random Forest classification performance across feature engineering configurations (5-fold CV, macro-averaged).

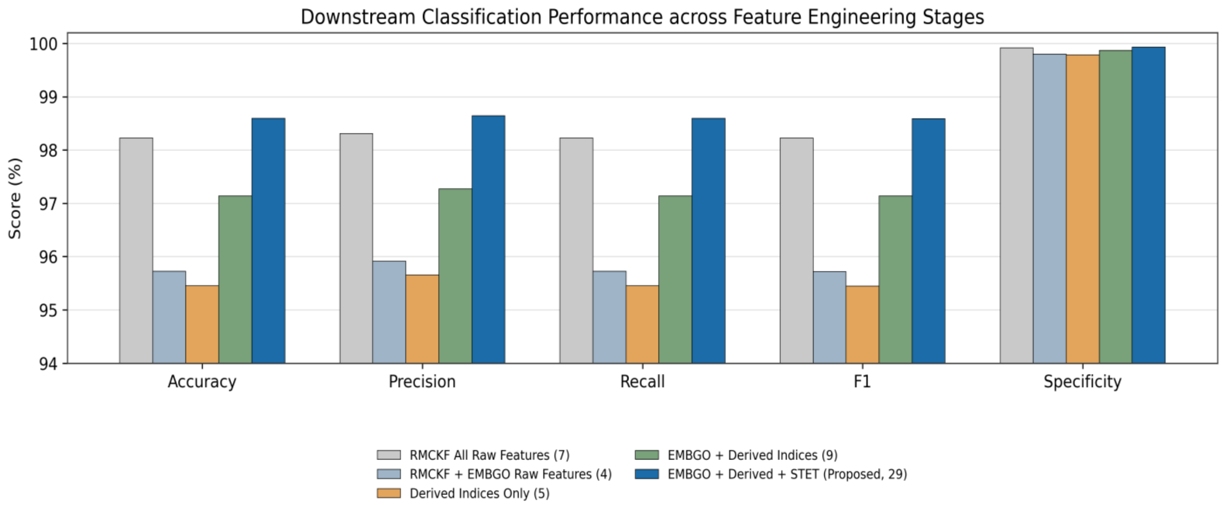

Fig. 5. Classification performance comparison across feature engineering stages.

D. Ablation: Harmonic vs. Transient STET Components

Table III isolates the contribution of the STET harmonic descriptors (instantaneous frequency/amplitude from the STFT ridge) and transient descriptors (Hilbert-based instantaneous amplitude/frequency). The harmonic-only configuration (98.41% accuracy) outperforms the transient-only configuration (97.82%), indicating that the slowly varying, periodic structure of environmental stress indicators carries more classification-relevant information than abrupt local fluctuations for this dataset; combining both yields the best overall result (98.59%), confirming the two descriptor families are complementary rather than redundant.

STET Configuration	**Acc.(%)**	**Prec.(%)**	**Rec.(%)**	**F1(%)**	**Dim.**
Harmonic Only (InstFreq+InstAmp)	98.41	98.47	98.41	98.41	19
Transient Only (HilAmp+HilFreq)	97.82	97.92	97.82	97.81	19
Both (Proposed)	98.59	98.64	98.59	98.59	29

TABLE III. Ablation of STET harmonic and transient descriptor components.

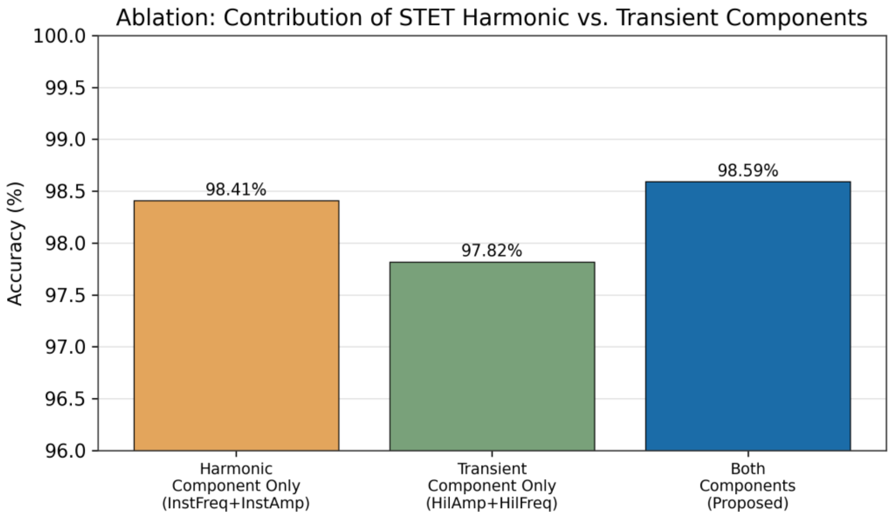

Fig. 6. Accuracy contribution of STET harmonic vs. transient descriptor components.

E. Discussion

These results support three observations. First, domain-grounded derived indicators alone are not sufficient to outperform a well-selected raw feature set; their value is realized only once time-frequency descriptors expose the local dynamics of each indicator stream. Second, the harmonic (ridge-based) descriptors are individually more informative than the transient (Hilbert-based) descriptors on this dataset, though both contribute. Third, the full proposed engineered set surpasses even the unreduced 7-feature raw baseline, suggesting that the feature-engineering stage successfully compensates for the dimensionality reduction performed during pre-processing while adding agronomic interpretability that raw sensor values alone do not provide.

VI. CONCLUSION

This paper proposed a feature-engineering stage for smart agriculture that derives five domain-grounded environmental stress indicators and applies a Synchro-Transient-Extracting Transform-style time-frequency decomposition to extract complementary harmonic and transient descriptors from each indicator stream. On a real 22-crop dataset, the resulting 29-dimensional engineered feature set achieved 98.59% classification accuracy, outperforming raw-feature baselines and a derived-indices-only configuration, with an ablation study confirming that both harmonic and transient descriptor families contribute complementary discriminative information. This engineered feature set forms the input to the final classification and environmental-stress-prediction stage of the overall smart-agriculture framework. Future work will feed this representation directly into the proposed Residual Multi-Fidelity Neural Network classifier and evaluate the complete end-to-end pipeline.

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