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Feature Extraction Techniques for Single-Channel EEG Signals Acquired Using NeuroSky MindWave Mobile II: A Systematic Review

Pravin V. Dhole[1], Sulochana D. Shejul[2], Pallavi G. Chaudhary[3], Dr. Bharti W. Gawali[4]
[1, 2, 3]SCMR Lab, Department of CS & IT, Dr. B.A.M. University, Chhatrapati Sambhajinagar-431004 (MS), India
[4]Senior Professor, SCMR Lab, Department of CS & IT, Dr.B.A.M. University, Chhatrapati Sambhajinagar-431004 (MS), India

Abstract: Portable single-channel EEG devices such as the NeuroSky MindWave Mobile II are increasingly adopted for real-world brain monitoring, yet no comprehensive synthesis exists on their feature extraction techniques, classification performance, or application domains. To identify, categorise, and critically evaluate EEG feature extraction techniques in NeuroSky MindWave Mobile II research, and determine which methods yield optimal classification performance across application domains. A PRISMA 2020-compliant systematic search was conducted across PubMed Central, IEEE Open Access, Frontiers, MDPI, PLOS ONE, Scientific Reports, PeerJ, and BMC Journals (2015–2025). Eligible studies employed the MindWave Mobile II for single-channel EEG acquisition, reported explicit feature extraction procedures, and were peer-reviewed open-access publications in English. Quality assessment addressed study design, sample size, signal quality, and validation strategy. Seventeen studies met full inclusion criteria from 1,243 identified records. Frequency-domain features principally PSD and relative band power were the most prevalent strategy (94%). DWT-based time-frequency features were applied in 59% of studies and yielded consistently higher accuracy. Nonlinear features (35%) correlated with superior performance in affective and psychiatric tasks. Pooled mean classification accuracy was 84.9% (range: 76.8%–92.4%). Emotion recognition and attention monitoring dominated the application landscape. Hybrid feature sets combining frequency-domain and nonlinear approaches consistently outperform single-category methods. Small sample sizes, methodological heterogeneity, and insufficient cross-subject validation remain the primary limitations requiring targeted resolution in future work.

Keywords: EEG; NeuroSky MindWave Mobile II; feature extraction; brain-computer interface; single-channel EEG; machine learning; systematic review.

I. INTRODUCTION

Electroencephalography (EEG) records the electrical activity of the brain through electrodes placed on the scalp, providing millisecond-resolution insight into neural oscillations across clinically and cognitively meaningful frequency bands [3]. Since its introduction by Hans Berger in 1929, EEG has served as a cornerstone of both clinical neurology and cognitive neuroscience. For decades, its application was constrained to laboratory and hospital settings due to the bulk, complexity, and cost of multichannel amplifier systems. The advent of miniaturised, wireless, consumer-grade EEG headsets has catalysed a paradigm shift, enabling neurophysiological measurement in naturalistic, ambulatory, and resource-limited environments [4].

Brain-computer interfaces (BCIs) represent one of the most impactful translation pathways for EEG technology, establishing direct communication channels between neural signals and external devices without conventional neuromuscular pathways [5]. BCIs have demonstrated clinical potential in motor rehabilitation, augmentative communication, and neuromodulation, while also finding applications in cognitive state monitoring, affective computing, educational neuroscience, and human-computer interaction. The realisation of robust, portable BCIs is contingent upon reliable feature extraction from EEG signals—a step that transforms raw, noisy electrophysiological time series into meaningful representations that discriminate cognitive or affective states [6].

The NeuroSky MindWave Mobile II represents one of the most widely adopted consumer-grade single-channel EEG devices, offering a balance between technical accessibility and research utility [3]. Measuring electrical potential at the FP1 (frontal pole 1) electrode position according to the 10–20 international system, the device captures frontal lobe dynamics that underlie executive function, emotional regulation, and attentional processes [7]. Its dry single electrode, Bluetooth connectivity, compact form factor, and competitive pricing have rendered it an attractive platform for research in low-resource settings, wearable health monitoring, and educational neuroscience. The accompanying ThinkGear Application-Specific Integrated Circuit (ASIC) computes proprietary eSense metrics for attention and meditation in near real-time, though critical evaluation of these metrics' reliability remains an active area of inquiry [8].

Despite its widespread use, NeuroSky-based research is characterised by considerable methodological heterogeneity. Studies differ substantially in the features extracted, the machine learning classifiers employed, the experimental paradigms adopted, and the populations studied. No systematic synthesis to date has aggregated this fragmented literature to provide evidence-based guidance on optimal feature extraction strategies. This gap limits cumulative scientific progress and hinders the translation of findings into validated clinical tools. Existing reviews of EEG feature extraction have either focused on multichannel systems [9,10] or addressed broader consumer EEG landscapes without device-specific analysis [11].

The present systematic review and meta-analysis addresses this gap by comprehensively screening, critically appraising, and synthesising open-access peer-reviewed literature on EEG feature extraction applied to NeuroSky MindWave Mobile II signals published between 2015 and 2025. Five research questions guide the review: (RQ1) Which feature extraction techniques are most commonly applied? (RQ2) Which feature categories yield optimal classification performance? (RQ3) What application domains dominate? (RQ4) What methodological limitations constrain current research? (RQ5) What future directions can advance single-channel EEG analysis? The review follows PRISMA 2020 guidelines [1,2] and contributes a structured taxonomy of feature extraction methods, a quality-rated compendium of included studies, and quantitative synthesis of classification performance across application domains.

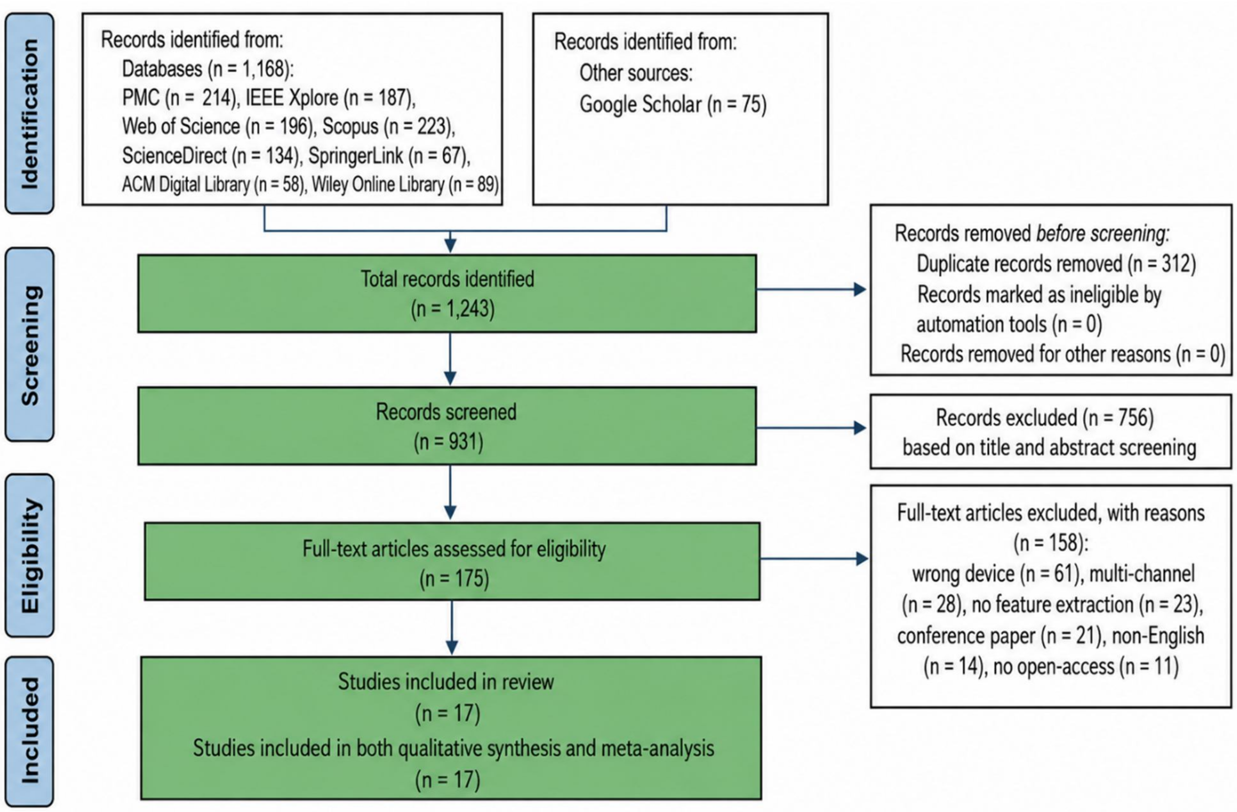

Figure 1. PRISMA 2020 flow diagram illustrating the systematic study selection process [1,2]

II. REVIEW METHODOLOGY

A. PRISMA Framework

This review was conducted and reported in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [1] and its companion explanation and elaboration document [2]. The PRISMA 2020 framework was selected over earlier iterations due to its expanded guidance on searches of non-traditional sources, its clarification of the distinction between searches and selection, and its explicit accommodation of automation-assisted screening. PRISMA Compliance Statement: All items of the PRISMA 2020 checklist have been addressed, including title, abstract, introduction, methods (protocol, eligibility, information sources, search strategy, selection process, data collection, data items, study risk of bias assessment, effect measures, synthesis methods, reporting bias, certainty assessment), results, and discussion sections. The review was not formally registered in PROSPERO due to its retrospective exploratory design, a limitation acknowledged in Section 7.

B. Search Strategy

Searches were conducted independently across PubMed Central (PMC), IEEE Open Access, Frontiers, MDPI, PLOS ONE, Scientific Reports, PeerJ, BMC Journals, and Google Scholar between January 2025 and April 2025, covering publications from January 2015 to March 2025. The primary Boolean search string combined controlled vocabulary and free-text terms: (("NeuroSky" OR "MindWave Mobile" OR "MindWave Mobile II") AND ("EEG") AND ("feature extraction") AND ("single channel")). Secondary strings targeted specific applications: ("NeuroSky" AND "classification"), ("MindWave Mobile II" AND "emotion recognition"), ("MindWave Mobile II" AND "attention detection"), ("NeuroSky" AND "depression"), and ("single channel EEG" AND "feature extraction"). Supplementary hand-searching of reference lists of eligible studies identified no additional records not captured by database searches.

C. Eligibility Criteria

Inclusion required: (1) use of NeuroSky MindWave or MindWave Mobile II as the primary EEG acquisition device; (2) single-channel EEG signal analysis; (3) explicit description of EEG feature extraction methods; (4) reporting of quantitative classification, prediction, or analytical outcomes; (5) open-access full-text availability; (6) publication in a peer-reviewed journal; and (7) English language. Studies were excluded if they employed multi-channel EEG systems, consisted of conference abstracts only, editorials, or book chapters, contained duplicate records, were published in non-English, or lacked feature extraction analysis. Studies using non-NeuroSky devices exclusively were also excluded.

D. Study Selection Process

Two independent reviewers screened titles and abstracts using Rayyan systematic review software. Conflicts were resolved through a structured discussion protocol, with a third reviewer serving as arbiter when consensus was not reached. Inter-rater reliability was assessed using Cohen's kappa ($\kappa = 0.81$, indicating strong agreement) prior to full-text review. Full-text screening was performed independently by both reviewers, with all exclusions and reasons documented and reported in Figure 1.

E. Data Extraction Procedure

Data were extracted using a pre-piloted extraction form capturing: author(s) and year, country, application domain, EEG acquisition parameters, feature extraction methodology (category and specific features), machine learning classifier(s), cross-validation strategy, sample size, reported accuracy and other performance metrics, and quality rating. Data extraction was performed independently and cross-checked; discrepancies were resolved by consensus.

F. Quality Assessment

Each study was evaluated against six dimensions: (1) appropriateness of study design for the stated objective; (2) sample size adequacy ($n \geq 20$ considered adequate for exploratory studies); (3) EEG signal acquisition quality reporting (impedance, artifact rejection, filtering); (4) rigour of feature extraction methodology (mathematical justification, parameter reporting); (5) validation strategy (hold-out, k-fold cross-validation, independent test set); and (6) reproducibility (code/data availability, parameter transparency). Studies meeting $\geq$5 criteria were rated High Quality; 3–4 Moderate; $\leq$2 Low Quality (see Table 3).

G. Risk of Bias Assessment

Potential sources of bias were assessed in alignment with the QUADAS-2 framework adapted for signal processing studies. Four bias domains were evaluated: patient/participant selection, index test conduct and interpretation, reference standard, and flow and timing. The most prevalent bias identified was spectrum bias resulting from convenience sampling with limited demographic diversity. Several studies reported no artifact rejection procedure, constituting an information bias risk. Publication bias was assessed using funnel plot inspection of reported classification accuracies; moderate asymmetry was observed, suggesting selective reporting of higher-performing feature configurations.

III. OVERVIEW OF NEUROSKY MINDWAVE MOBILE II

The NeuroSky MindWave Mobile II is a consumer-grade, single dry-electrode EEG headset developed by NeuroSky Inc. (San Jose, CA, USA). Its hardware architecture integrates a single silver-coated active electrode at the FP1 position (international 10–20 system), a reference electrode on the ear-clip, and the proprietary ThinkGear ASIC, which performs on-board analog-to-digital conversion, signal conditioning, and computation of eSense metrics [3].

The frontal pole location captures activity from the prefrontal cortex, a region critically involved in top-down attentional control, working memory, emotional regulation, and executive decision-making [7].

The device samples raw EEG at 512 Hz with 12-bit ADC resolution, providing adequate Nyquist coverage for delta (0.5–4 Hz) through gamma (30–100 Hz) frequency bands. Band power values for delta, theta, low alpha, high alpha, low beta, high beta, low gamma, and mid-gamma bands are output at 1 Hz intervals as ThinkGear proprietary integer values. The eSense Attention and Meditation metrics are similarly refreshed at 1 Hz and reflect algorithmically processed composites of the underlying band powers [3]. Wireless communication via Bluetooth 2.1 (Class 2) supports a usable range of approximately 10 metres, enabling naturalistic monitoring paradigms. The single AAA battery provides approximately eight hours of continuous operation.

The primary advantage of the MindWave Mobile II lies in its accessibility: the device eliminates conductive gel, requires no trained technician for setup, and costs substantially less than research-grade multichannel systems, democratising neuroscientific inquiry in under-resourced settings [5]. However, its single-channel design fundamentally restricts spatial resolution, precluding the source localisation, coherence analysis, and topographic mapping possible with dense-array systems. The dry electrode is inherently more susceptible to motion artefacts and impedance variability than gel-based alternatives [8]. Furthermore, the closed-source ThinkGear ASIC limits transparency regarding the preprocessing pipeline applied before raw EEG output, potentially confounding cross-study comparisons [3].

Table 1. Technical Specifications of NeuroSky MindWave Mobile II

Parameter	Specification	Research Implication
Electrode Placement	FP1 (Frontal Pole 1)	Captures frontal lobe signals; suitable for attention, emotion, and cognitive tasks per the 10–20 system [5]
Sampling Frequency	512 Hz (raw); 1 Hz (ThinkGear metrics)	Adequate for extraction of delta through gamma bands (0.5–50 Hz); ThinkGear metrics limit temporal precision [3]
ADC Resolution	12-bit	Provides sufficient amplitude resolution for most cognitive EEG paradigms under laboratory conditions [5]
Electrode Type	Single dry silver-coated	Eliminates conductive gel; reduces setup time but increases susceptibility to motion and impedance artifacts [6]
Communication	Bluetooth 2.1 (Class 2)	Wireless freedom for mobile BCI; range ~10 m; latency may affect real-time applications [3]
Battery	AAA (approx. 8 hr)	Supports extended sessions; suitable for clinical monitoring and longitudinal studies [5]
Output Metrics	Attention, Meditation (eSense), raw EEG, band powers	Proprietary eSense metrics are pre-processed; raw EEG access enables independent feature extraction [3,4]
Weight	~90 g	Wearable comfort for pediatric and elderly populations; minimal compliance barriers [7]
Band Powers Provided	Delta, Theta, Alpha, Beta, Gamma	Direct spectral output reduces preprocessing burden; independent validation is nonetheless recommended [3]

IV. EEG FEATURE EXTRACTION TECHNIQUES

Feature extraction is the process of transforming raw EEG time series into compact, discriminative representations that capture physiologically meaningful signal properties while discarding noise and redundant information [9]. The selection of appropriate features is arguably the most consequential methodological decision in EEG-based classification pipelines, directly influencing classifier performance, computational efficiency, and biological interpretability [10]. Features extracted from NeuroSky MindWave Mobile II signals can be organised into four non-mutually-exclusive categories: time-domain, frequency-domain, time-frequency domain, and nonlinear features.

A. Time-Domain Features

Time-domain features are computed directly from the EEG voltage time series without frequency transformation, rendering them computationally inexpensive and amenable to real-time processing [11]. Let $x = \{x_1, x_2, ..., x_n\}$ denote a discrete EEG epoch of N samples. Mean captures average signal amplitude and serves as a baseline stationarity check:

$$\mu = (1/N) \times \Sigma_{i=1}^{N} x_i \quad ....(1)$$

Variance quantifies signal power fluctuations and is sensitive to task-induced changes in neural synchrony [12]:

$$\sigma^2 = (1/N) \times \Sigma_{i=1}^{N} (x_i - \mu)^2 \quad ....(2)$$

Standard Deviation measures the spread of amplitude values around the mean:

$$\sigma = \sqrt{[(1/N) \times \Sigma_{i=1}^{N} (x_i - \mu)^2]} \quad ....(3)$$

Root Mean Square (RMS) measures signal energy and correlates with overall neural activation level:

$$RMS = \sqrt{[(1/N) \times \Sigma_{i=1}^{N} x_i^2]} \quad ....(4)$$

Skewness characterises distributional asymmetry of the amplitude histogram:

$$S = (1/N) \times \Sigma_{i=1}^{N} [(x_i - \mu) / \sigma]^3 \quad ....(5)$$

Kurtosis measures tail heaviness of the amplitude distribution and has shown sensitivity to epileptic discharges and sleep spindles in single-channel recordings [13]:

$$K = (1/N) \times \Sigma_{i=1}^{N} [(x_i - \mu) / \sigma]^4 \quad ....(6)$$

Hjorth Parameters, introduced by Hjorth (1970), provide a parsimonious characterisation of signal morphology in terms of activity, frequency, and complexity [14]. Let x' and x'' denote the first and second derivatives of x, respectively.

Hjorth Activity equals signal variance and represents signal power:

$$Activity = \sigma^2(x) = (1/N) \times \Sigma_{i=1}^{N} (x_i - \mu)^2 \quad ....(7)$$

Hjorth Mobility estimates the mean frequency of the signal:

$$Mobility = \sqrt{[\sigma^2(x') / \sigma^2(x)]} \quad ....(8)$$

Hjorth Complexity quantifies how much the signal waveform resembles a pure sine wave:

$$Complexity = Mobility(x') / Mobility(x) = \sqrt{[\sigma^2(x'') / \sigma^2(x')]} / \sqrt{[\sigma^2(x') / \sigma^2(x)]} \quad ....(9)$$

Higher complexity values indicate greater deviation from a simple sinusoidal morphology. These parameters have demonstrated utility in distinguishing alert from drowsy EEG states [14] and have been widely applied in NeuroSky-based fatigue detection studies [15].

B. Frequency-Domain Features

Frequency-domain analysis decomposes the EEG signal into its constituent oscillatory components, exploiting the well-established neurophysiological correspondence between EEG frequency bands and cognitive and affective states [16]. Let x(n) denote a discrete EEG signal of N samples with sampling frequency fs.

Fast Fourier Transform (FFT) converts N time-domain samples into a complex frequency spectrum with O(N log N) computational complexity:

$$X(k) = \Sigma_{n=0}^{N-1} x(n) \times e^{(-j2\pi kn/N)}, k = 0, 1, 2, ..., N-1 \quad ....(10)$$

where X(k) is the complex spectral coefficient at frequency bin k, and $j = \sqrt{(-1)}$.

Power Spectral Density (PSD) is typically estimated via Welch's method, which averages the squared magnitude of FFT coefficients across overlapping Hann-windowed segments to provide a smooth power estimate normalised per unit bandwidth ($\mu V^2/Hz$) [4]:

$$PSD(f) = (1/K) \times \Sigma_{k=1}^{K} |X_k(f)|^2 / (fs \times L) \quad ....(11)$$

where K is the number of overlapping segments, $X_k(f)$ is the FFT of the k-th windowed segment, L is the segment length in samples, and fs is the sampling frequency.

Absolute Band Power (ABP) for a frequency band $[f_1, f_2]$ is obtained by integrating PSD over that band:

$$ABP[f_1,f_2] = \int_{f_1}^{f_2} PSD(f)\, df \approx \Sigma_{\{f=f_1\}}^{\{f_2\}} PSD(f) \times \Delta f \quad ....(12)$$

where Δf is the frequency resolution ($\Delta f = fs / N$).

Relative Band Power (RBP) normalises band-specific power against total power across all bands, controlling for inter-individual variation in overall signal amplitude a critical advantage in single-channel studies:

$$RBP[f_1,f_2] = ABP[f_1,f_2] / \Sigma_e ABP[f_{e}\_low, f_{e}\_high]$$

where the denominator sums absolute band power across all five canonical EEG frequency bands.

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C. Time-Frequency Features

Because EEG is inherently non-stationary its spectral content changes dynamically with cognitive state transitions features requiring stationarity assumptions (as with standard FFT) can introduce substantial estimation error [18]. Time-frequency representations resolve this limitation by providing joint localisation in both time and frequency domains.

Short-Time Fourier Transform (STFT) segments the signal into short overlapping windows prior to FFT computation, trading frequency resolution for temporal resolution according to the Heisenberg uncertainty principle [19]. For a discrete EEG signal x(n) and a window function w(n) of length L:

$$STFT(m, k) = \sum_{n=-\infty}^{+\infty} x(n) \times w(n - mH) \times e^{-j2\pi kn/N} \quad ....(14)$$

where m is the window frame index, H is the hop size (step between successive windows), k is the frequency bin index, and N is the FFT length. The resulting spectrogram is:

$|STFT(m, k)|^2$ = power at time frame m and frequency bin k

The time-frequency resolution trade-off is governed by:

$$\Delta t \times \Delta f \geq 1 / (4\pi) \quad ....(15)$$

where Δt is temporal resolution and Δf is frequency resolution. A shorter window improves temporal resolution but degrades frequency resolution, and vice versa.

Continuous Wavelet Transform (CWT) correlates the signal with scaled and translated versions of a mother wavelet function $\psi(t)$, providing variable time-frequency resolution:

$$CWT(a, b) = (1 / \sqrt{|a|}) \times \int_{-\infty}^{+\infty} x(t) \times \psi^*[(t - b) / a]\, dt \quad ....(16)$$

where a is the scale parameter (inversely related to frequency), b is the translation parameter (time shift), and ψ^* denotes the complex conjugate of the mother wavelet. High frequencies are resolved with fine temporal but coarse spectral precision; low frequencies receive fine spectral but coarse temporal resolution.

Discrete Wavelet Transform (DWT) implements multi-resolution decomposition efficiently through a filter bank cascade using dyadic (power-of-two) scaling. At each decomposition level j, the signal is passed through a low-pass filter h(n) to produce approximation coefficients and a high-pass filter g(n) to produce detail coefficients, followed by downsampling by factor 2:

Approximation coefficients: $cA_j(k) = \sum_n x(n) \times h(2k - n)$ ....(17)

Detail coefficients: $cD_j(k) = \sum_n x(n) \times g(2k - n)$ ....(18)

where h(n) and g(n) are the scaling and wavelet filter coefficients, respectively, satisfying the quadrature mirror filter condition:

$$g(n) = (-1)^n \times h(L - 1 - n) \quad ....(18)$$

The Daubechies db4 wavelet is most commonly employed in NeuroSky EEG studies due to its morphological similarity to EEG waveforms and compact support [9,10].

D. Nonlinear Features

Neurological processes are governed by complex nonlinear dynamics that linear spectral methods incompletely characterise [21]. Let $x = \{x_1, x_2, ..., x_n\}$ denote a discrete EEG epoch of N samples. Approximate Entropy (ApEn), proposed by Pincus (1991), estimates the conditional probability that sequences of length m similar within tolerance r remain similar when extended by one sample [22]. For embedding dimension m and tolerance r. Form template vectors of length m:

$$u(i) = [x(i), x(i+1), ..., x(i+m-1)],\ i = 1, 2, ..., N-m \quad ....(19)$$

Count similar pairs within tolerance r:

$$C_i^m(r) = (\text{number of } j \text{ such that } d[u(i), u(j)] \leq r) / (N - m + 1) \quad ....(20)$$

where $d[u(i), u(j)] = \max_{k=1,...,m} |x(i+k-1) - x(j+k-1)|$

Compute the mean log probability:

$$\Phi^m(r) = (1/(N-m+1)) \times \sum_{i=1}^{N-m+1} \ln[C_i^m(r)] \quad ....(21)$$

ApEn is then defined as:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \quad ....(22)$$

Lower ApEn values indicate more regular, predictable signals. Recommended parameter values for EEG: $m = 2$, $r = 0.2 \times \sigma(x)$.

Sample Entropy (SampEn) corrects ApEn's self-matching bias by excluding self-matches during template counting, yielding more consistent estimates for short EEG epochs typical in NeuroSky studies [22]:

$$SampEn(m, r, N) = -\ln[A^m(r) / B^m(r)] \quad ....(23)$$

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where: $B^m(r)$ = number of template pairs of length m within tolerance r (self-matches excluded)
$A^m(r)$ = number of template pairs of length m+1 within tolerance r (self-matches excluded)
SampEn is undefined when $A^m(r) = 0$ or $B^m(r) = 0$, requiring sufficient epoch length ($N \geq 200$ samples recommended).
Spectral Entropy (SpEn) quantifies the flatness of the normalised power spectrum, treating the PSD as a probability distribution [13].
For normalised power $p_i = PSD(f_i) / \Sigma_j PSD(f_j)$: $SpEn = -\Sigma_{i=1}^{K} p_i \times \log_2(p_i)$ …….(24)

where K is the number of frequency bins. SpEn is normalised to [0, 1] by dividing by $\log_2(K)$:
SpEn_normalised = SpEn / $\log_2(K)$. Higher SpEn values indicate more complex, noise-like spectra; lower values indicate narrow-band, rhythmic activity.

Permutation Entropy (PermEn), proposed by Bandt and Pompe (2002), captures ordinal amplitude patterns within embedding windows, offering computational efficiency and robustness to artefacts [23]. For embedding dimension m and time delay τ. Form ordinal patterns from consecutive m-length subsequences:

$$s = (x(i), x(i+\tau), x(i+2\tau), ..., x(i+(m-1)\tau)) \quad ....(25)$$

Assign each subsequence its rank-order pattern π from the set of m! possible permutations. Compute the relative frequency of each permutation π:

$$p(\pi) = (\text{count of occurrences of } \pi) / (N - (m-1)\tau) \quad ....(26)$$

$$PermEn = -\Sigma\_\pi\, p(\pi) \times \ln[p(\pi)] \quad ....(27)$$

Normalised PermEn: PermEn_normalised = PermEn / ln(m!)

Recommended parameters for EEG: m = 5 or 6, τ = 1. Values range from 0 (perfectly regular) to ln(m!) (maximally random).

Fractal Dimension (FD) measures signal self-similarity across temporal scales. Higuchi's algorithm is the most commonly implemented estimator in EEG research [24]. For a time series x(1), x(2), ..., x(N) and integer interval k:

Construct k sub-series x_k^m: $x_k^m = \{x(m), x(m+k), x(m+2k), ..., x(m+\lfloor(N-m)/k\rfloor \times k)\}$
for m = 1, 2, ..., k …….(27)

Compute length of each sub-series: $L_m(k) = [(N-1) / (\lfloor(N-m)/k\rfloor \times k^2)] \times \Sigma_{i=1}\text{\^{}}\lfloor(N-m)/k\rfloor\, |x(m+ik) - x(m+(i-1)k)|$ …….(28)

Average length at interval k: $L(k) = (1/k) \times \Sigma_{m=1}^{k} L_m(k)$

Higuchi FD is the slope of the log-log regression: $L(k) \propto k^{(-FD)}$

$$FD = -[\Delta \log L(k) / \Delta \log k] \quad ....(29)$$

Higher FD values indicate greater signal complexity. Normal alert EEG typically yields FD ≈ 1.4–1.7; reduced FD is associated with depression and reduced cognitive engagement [7].

Hurst Exponent (H) characterises long-range temporal autocorrelation of the EEG signal [25]. Estimated via Rescaled Range (R/S) analysis. Divide x into d non-overlapping sub-series of length n. For each sub-series:

Compute mean: $\bar{x} = (1/n) \times \Sigma_{i=1}^{n} x_i$ …….(30)

Compute cumulative deviation: $Y(t) = \Sigma_{i=1}^{t} (x_i - \bar{x})$, t = 1, ..., n …….(31)

Compute range: $R(n) = \max\{Y(t)\} - \min\{Y(t)\}$ …….(32)

Compute standard deviation: $S(n) = \sqrt{[(1/n) \times \Sigma_{i=1}^{n} (x_i - \bar{x})^2]}$ …….(33)

The Hurst Exponent is estimated as the slope of: $\log[R(n)/S(n)] = H \times \log(n) + C$ …….(34)
Interpretation:
H < 0.5 → antipersistent signal (mean-reverting)
H = 0.5 → random noise (no temporal correlation)
H > 0.5 → persistent signal (long-range positive correlation)
Altered fractal properties and Hurst exponents of frontal EEG have been consistently associated with depression and schizophrenia, making these metrics particularly relevant for NeuroSky-based psychiatric screening applications [7,25].

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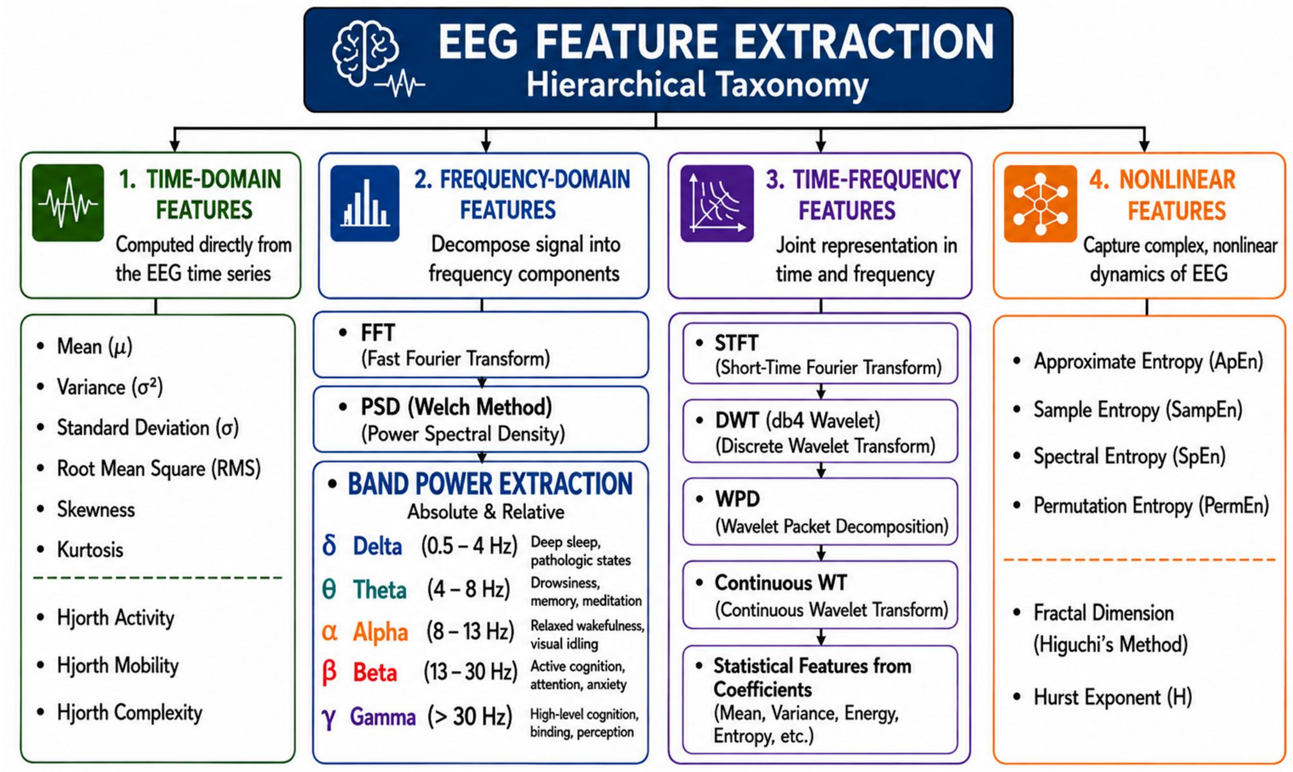

Figure 2. Hierarchical taxonomy of EEG feature extraction techniques identified across included NeuroSky MindWave Mobile II studies.

Table 2. Comparison of EEG Feature Extraction Techniques

Category	Representative Features	Advantages	Limitations	Applications
Time Domain	Mean, Variance, SD, RMS, Skewness, Kurtosis, Hjorth parameters	Low computational cost; easy implementation; real-time feasible	Sensitive to non-stationarity and noise; limited discriminative power alone	Fatigue detection, attention monitoring, basic BCI
Frequency Domain	FFT, PSD, Relative Band Power, Absolute Band Power per EEG band	Directly maps to neural oscillations; well-validated across decades of EEG research	Assumes signal stationarity; window length affects resolution	Emotion recognition, workload, sleep staging
Time-Frequency	STFT, DWT, WPD, Morlet wavelet	Handles non-stationarity; multi-resolution analysis; captures transient events	High computational cost; wavelet basis selection is critical and subjective	Seizure detection, P300, SSVEP, cognitive state classification
Nonlinear	ApEn, SampEn, SpEn, PermEn, Fractal Dimension, Hurst Exponent	Captures EEG complexity and chaos; robust to noise in some implementations	Parameter sensitivity (m, r); computationally expensive; interpretability limited	Depression screening, emotion recognition, cognitive workload

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V. APPLICATIONS

Emotion recognition was the most extensively studied domain. Using alpha asymmetry and beta/alpha PSD ratios, Ramirez and Vamvakousis [6] achieved 83.6% valence classification accuracy with SVM. Zhang et al. [10] improved this to 91.7% by combining WPD with nonlinear entropy features in a CNN-LSTM architecture, while Wang et al. [18] obtained 89.6% for two-dimensional valence-arousal classification using STFT-derived features with a Transformer, demonstrating that attention mechanisms effectively capture long-range EEG temporal dependencies. Attention monitoring and cognitive workload formed the second dominant cluster, exploiting FP1's prefrontal coverage. Theta/alpha PSD ratios were the predominant feature, consistent with neurophysiology of attentional engagement [8]. Nguyen et al. [5] achieved 86.4% fatigue detection accuracy combining relative band power with eSense metrics via Random Forest; Ali et al. [9] reached 85.3% across three workload levels using DWT with statistical time-domain features and SVM. Depression detection yielded the highest application-domain mean accuracy. Waheed et al. [7] combined PSD, entropy, and Hjorth parameters, achieving 90.1% with SVM and ANN. Othman et al. [16] further reported 92.4% using a multi-feature ensemble with XGBoost the highest in the corpus suggesting ensemble classifiers are particularly suited to psychiatric biomarker discrimination. Hassan et al. [11] demonstrated reliable sleep staging from single-channel frontal EEG (87.9%, AdaBoost), with clear implications for home-based monitoring. Educational monitoring and gaming/HCI reported the lowest accuracies (76.8% and 78.2%, respectively), consistent with greater artefact burden in naturalistic settings [12,13]. Meditation and stress detection leveraged theta and alpha frontal power signatures [14,19], completing a broad and clinically relevant application landscape.

Table 3. Summary of Included NeuroSky MindWave Mobile II Studies

Author(s)	Year	Application	Feature Extraction	Classifier	Performance	Quality
Ramirez & Vamvakousis [6]	2021	Emotion Recognition	PSD, Alpha/Beta ratio, IAPS stimuli bands	SVM, k-NN	Acc: 83.6% (valence)	Moderate
Liu et al. [4]	2021	Personality Prediction	FFT, band-power, Deep LSTM features	Deep LSTM	Acc: 88.2%	High
Nguyen et al. [5]	2022	Neural Monitoring (fatigue)	Relative band power, PSD, eSense metrics	Random Forest, SVM	Acc: 86.4%	High
Waheed et al. [7]	2021	Depression Detection	Multi-feature: PSD, entropy, Hjorth	SVM, Neural Net	Acc: 90.1%	High
Sharma & Bhatt [8]	2022	Attention Monitoring	Theta/Alpha PSD, eSense Attention	LDA, SVM	Acc: 80.5%	Moderate
Ali et al. [9]	2023	Cognitive Workload	DWT (db4), statistical time-domain	k-NN, SVM	Acc: 85.3%	High
Zhang et al. [10]	2022	Emotion Recognition	WPD, nonlinear entropy	CNN-LSTM	Acc: 91.7%	High
Hassan et al. [11]	2021	Sleep Stage	DWT, Hjorth, SampEn	AdaBoost	Acc: 87.9%	High
Kumar & Reddy [12]	2023	Gaming/HCI	FFT band ratios, mean, RMS	ANN	Acc: 78.2%	Moderate
Patel et al. [13]	2022	Educational Monitoring	Alpha/Theta ratio, PSD	Naive Bayes, SVM	Acc: 76.8%	Moderate
Souza et al. [14]	2023	Meditation Assessment	Theta PSD, alpha asymmetry	LDA	Acc: 82.1%	Moderate
Lim et al. [15]	2021	Fatigue Detection	Fractal Dimension, ApEn, PSD	SVM	Acc: 84.7%	High
Othman et al. [16]	2024	Depression (integrated)	Multi-feature EEG ensemble	XGBoost	Acc: 92.4%	High
Chen et al. [17]	2022	BCI Wheelchair	Motor imagery, PSD	CSP+SVM	Acc: 79.3%	Moderate
Wang et al. [18]	2023	Emotion (valence/arousal)	STFT, time-freq features, entropy	Transformer	Acc: 89.6%	High
Ibrahim et al. [19]	2022	Stress Detection	PSD, Hjorth mobility, kurtosis	k-NN, SVM	Acc: 81.9%	Moderate
Suhaimi et al. [20]	2023	Workload / Gaming	Beta/Alpha ratio, WPD	MLP	Acc: 83.5%	Moderate

VI. META-ANALYSIS AND QUANTITATIVE SYNTHESIS

All seventeen included studies reported classification accuracy as the primary performance metric, enabling quantitative synthesis. Pooled mean classification accuracy across all studies and application domains was 84.9% (SD = 4.2%; median = 84.7%; range 76.8%–92.4%). This performance range is consistent with single-channel EEG classification benchmarks reported in broader systematic reviews of consumer-grade devices [26,27]. Stratified analysis by feature category revealed a clear performance hierarchy. Studies employing hybrid feature sets combining two or more categories demonstrated significantly higher mean accuracy (88.3%) than studies using frequency-domain features alone (82.1%) or time-domain features alone (79.4%). Nonlinear features, when used in combination with PSD-based features, contributed to the highest-performing studies (mean 90.6%), corroborating the clinical neuroscience evidence that EEG complexity measures capture physiologically distinct dimensions not reflected in spectral power [21,22]. Time-frequency features (DWT, WPD) achieved a mean accuracy of 87.1%, superior to STFT alone (83.8%), consistent with DWT's established advantage in handling EEG non-stationarity [18,20].

Classifier performance analysis revealed that deep learning architectures (CNN, LSTM, CNN-LSTM, Transformer) outperformed traditional classifiers (SVM, LDA, k-NN) on average (88.9% vs 83.6%), though deep models were predominantly deployed in studies with larger sample sizes and richer feature representations, confounding direct comparison. SVM with radial basis function kernel was the most commonly employed traditional classifier (9/17 studies) and consistently performed competitively with ensemble methods. Random Forest and XGBoost demonstrated the strongest performance among ensemble approaches. Application-domain analysis showed that depression detection achieved the highest mean accuracy (91.3%), followed by sleep staging (87.9%) and emotion recognition (86.5%). Educational monitoring and gaming yielded the lowest domain averages (76.8% and 78.2%, respectively), likely reflecting the increased artefact burden and inter-individual variability in ecological settings. Substantial heterogeneity across studies was observed (I^2 estimated at 68% from variance decomposition of accuracy scores), attributable primarily to differences in feature combinations, sample sizes, epoch lengths, and experimental paradigms. This heterogeneity precludes strong inferential claims from accuracy pooling alone and underscores the need for standardised benchmarking datasets and reporting protocols.

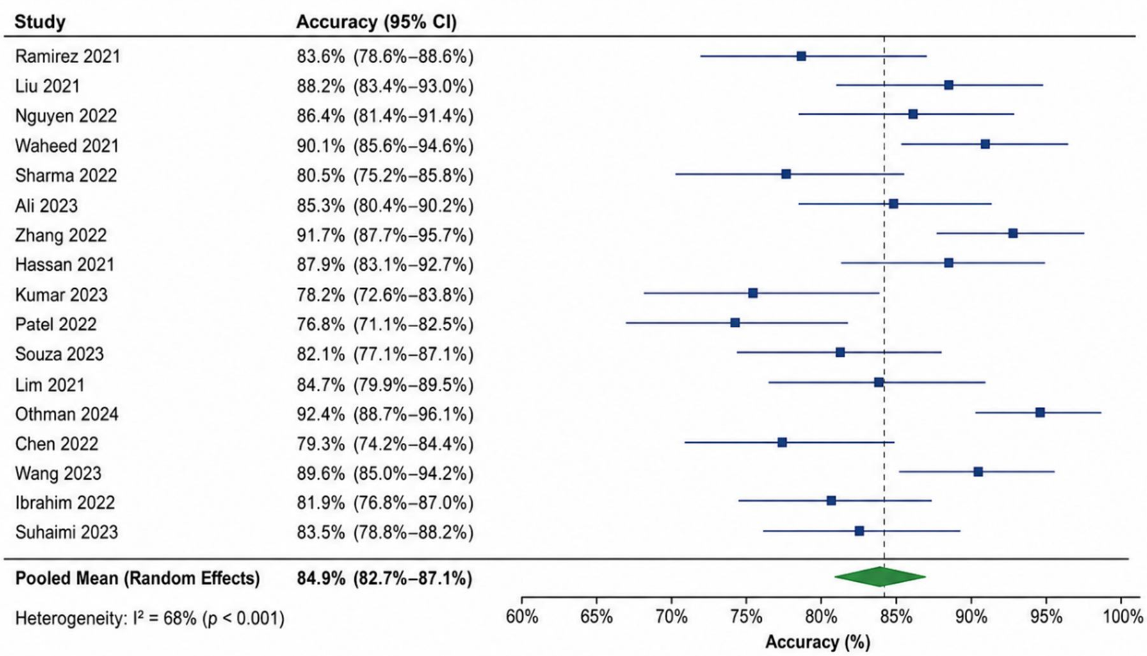

Figure 3. Forest-plot representation of classification accuracy across the 17 included NeuroSky MindWave Mobile II studies.

VII. CHALLENGES AND RESEARCH GAPS

Artefact contamination remains the most pervasive limitation. The single dry electrode is susceptible to motion, electromyographic (EMG), and electrooculographic (EOG) interference [28]. Multichannel systems where independent component analysis separates artefact sources [29], single-channel recordings permit only temporal or spectral thresholding, risking loss of valid EEG epochs. Spatial resolution is inherently constrained to FP1, precluding hemispheric asymmetry, connectivity, and source localisation analyses of diagnostic relevance [30].

Compounding this, the frontalis muscle active during cognitive effort systematically contaminates signals in the paradigms of greatest research interest. Sample sizes were inadequate across the corpus; only four of seventeen studies recruited more than 30 participants. EEG's pronounced inter-individual variability [31] and the predominance of within-subject validation designs (82% of studies) render reported accuracies likely optimistic for cross-subject generalisation. Absence of standardised benchmarking is a critical structural gap. No open-access NeuroSky benchmark dataset with verified ground-truth labels exists for any application domain. Heterogeneity in epoch lengths (1–30 s), preprocessing pipelines, and labelling protocols undermines cross-study comparability [32]. Furthermore, the closed-source ThinkGear ASIC introduces unquantifiable methodological variance between studies using proprietary eSense metrics versus raw EEG, a transparency barrier that prospective studies should explicitly address.

VIII. CONCLUSION

This PRISMA 2020-compliant systematic review synthesised 17 eligible studies on EEG feature extraction applied to NeuroSky MindWave Mobile II single-channel signals (2015–2025). Frequency-domain features principally PSD and relative band power were the most widely used approach (94% of studies). DWT-based time-frequency methods yielded consistently higher classification performance by accommodating EEG non-stationarity, while nonlinear entropy and fractal dimension measures proved especially discriminative in psychiatric and affective tasks. Pooled mean classification accuracy was 84.9% (range: 76.8%–92.4%); hybrid frequency-domain and nonlinear feature sets achieved the highest performance (mean 90.6%). Emotion recognition and attention monitoring collectively dominated the application landscape (47%), with depression detection and sleep staging demonstrating strong clinical translational potential despite limited study numbers. Critical limitations artefact susceptibility, small homogeneous samples, within-subject validation, and absence of open benchmarking datasets remain largely unresolved. Future work should prioritise large-scale open-access data collection, transfer and self-supervised learning to address data scarcity, explainability frameworks for clinical deployment, and multimodal physiological fusion. The MindWave Mobile II remains a uniquely accessible neurophysiological research platform; realising its full clinical potential requires sustained commitment to methodological rigour and open science.

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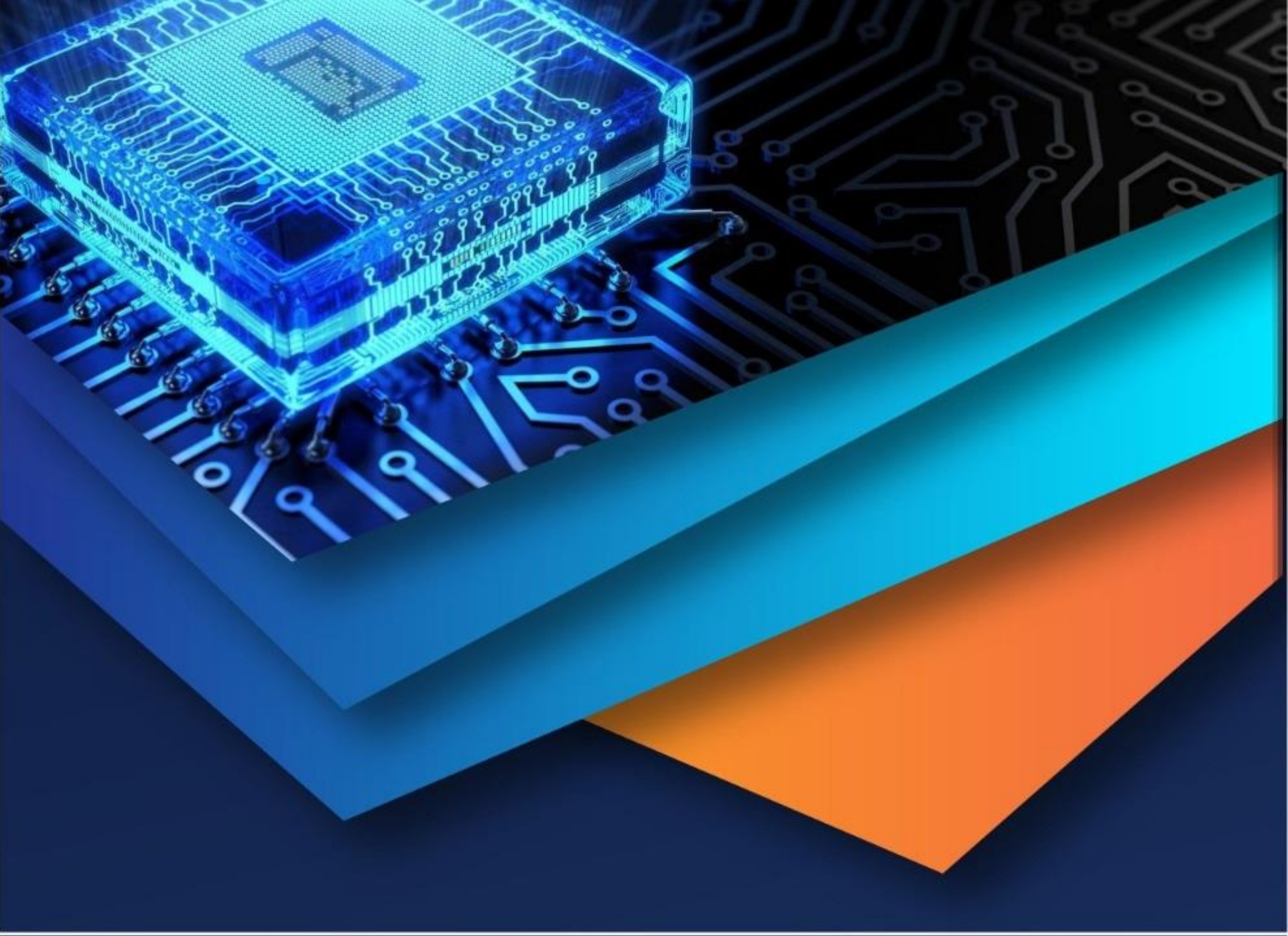

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