EEG Signal Processing and Machine Learning

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ABSTRACT

This report presents advanced signal processing and machine learning approaches for EEG-based performance prediction in golf putting. Building upon baseline preprocessing methodologies, three progressively sophisticated classification approaches were implemented: Logistic Regression (baseline), Random Forest with 152 Power Spectral Density features extracted using Welch's method, and 1D Convolutional Neural Networks for automatic temporal feature learning. Results demonstrate Random Forest achieved highest classification accuracy (66.0% mean test accuracy), followed by CNN at 61.0% exceeding baseline by 3 percentage points, and Logistic Regression at 58.0%. Statistical comparisons reveal medium effect size for RF versus LR (t=-1.81, p=0.104, Cohen's d=-0.57), small effect for CNN versus LR (p=0.496, d=-0.22), and small effect for CNN versus RF (p=0.453, d=0.25). The CNN's mean F1 score (0.113) reflects class prediction challenges due to class imbalance, though test accuracy remains competitive. Feature importance analysis reveals frontal theta/beta ratios and parietal spectral metrics as most discriminative for performance prediction. Environmental factors demonstrate moderate correlation with both behavioural performance and classification accuracy (r=0.605, p=0.066), establishing data quality as a critical determinant of model success. These findings validate that domain-engineered PSD features with ensemble methods achieve optimal performance while deep learning provides competitive results without manual engineering, establishing CNN viability when domain expertise is unavailable.

Keywords

Electroencephalogram (EEG) signal processing, Power Spectral Density, Logistic Regression (LR), Random Forest (RF), Convolutional Neural Networks (CNN), deep learning, feature importance, sports performance, machine learning

1. INTRODUCTION

Electroencephalography (EEG) provides non-invasive measurement of cortical electrical activity, enabling investigation of neural correlates underlying human performance. Previous research has established relationships between pre-movement brain activity patterns and subsequent motor task outcomes [1]. This project investigates whether machine learning classification models can predict sports performance in golf putting success from EEG signals recorded during the pre-execution period immediately preceding the motor act.

Understanding the neuroscientific foundations of these frequency patterns is essential for principled feature engineering and results interpretation. EEG signals decompose into canonical frequency bands: delta (0.5-4 Hz) for deep sleep, theta (4-8 Hz) for drowsiness, meditation, and memory encoding, alpha (8-13 Hz) for relaxed wakefulness and optimal performance states, beta (13-30 Hz) for active cognition and motor preparation, and gamma (30-100+ Hz) for higher-order cognitive integration [1]. The theta/beta ratio serves as an established marker of cognitive engagement and attentional control, with lower ratios indicating enhanced focus [5].

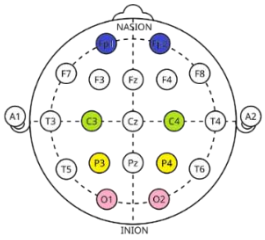

Figure 1 Electrode diagram – International 10-20 system

The International 10-20 electrode placement system (Figure 1) with eight channels provided comprehensive monitoring: frontal sites (Fp1, Fp2) for executive control, central locations (C3, C4) for motor planning and execution, parietal placements (P3, P4) for sensorimotor integration, and occipital electrodes (O1, O2) for visual processing.

Previous baseline analysis using 24 features with Logistic Regression achieved 59% test accuracy. Event-Related Potential (ERP) analysis revealed frontal and central channel differences between successful (Hit) and unsuccessful (Miss) trials, motivating advanced frequency-domain investigation. This work contributes: extraction of 152 advanced PSD features using Welch's method [2], Random Forest classification [3] with hyperparameter optimization, comprehensive feature importance analysis, rigorous three-model statistical comparison with effect size quantification, environmental factors investigation, and 1D CNN implementation enabling empirical comparison between traditional machine learning with hand-crafted features versus modern deep learning with learned representations.

2. METHODS

2.1 Experimental Design and Dataset

EEG data were recorded using a Mentalab Explore Pro wireless system during indoor golf putting tasks. The amplifier supports eight-channel acquisition (Fp1, Fp2, C3, C4, P3, P4, O1, O2) with 500 Hz sampling rate and 24-bit resolution. The lightweight design and wireless transmission capability enable naturalistic movement without cable artifacts, critical for studying motor performance in ecologically valid conditions.

The dataset comprises 10 experimental sessions conducted across three days, with 50 putting attempts per session yielding 500 total

trials. Post-hoc behavioural classification identified 321 successful putts (64.2% Hit rate) and 179 unsuccessful attempts (35.8% Miss rate). Environmental conditions were documented for each session including electrode-scalp impedance measurements, ambient lighting characteristics, and participant physiological state. The 64/36 class imbalance necessitates stratified sampling and balanced class weighting in classifier training.

Experimental sessions varied substantially in data quality. Session 50-5 represented optimal conditions with controlled impedance maintained in the ideal range (12-20 kΩ) and stable recording environment. Sessions 50-8 through 50-10 exhibited quality challenges from sunlight interference creating impedance fluctuations and participant hunger states potentially affecting both task performance and neural signatures. This natural variation enables investigation of environmental impact on classification performance, directly relevant for real-world deployment where controlled laboratory conditions cannot be guaranteed.

2.2 Signal Preprocessing Pipeline

Raw EEG signals underwent systematic preprocessing to remove artifacts while preserving task-relevant neural information. Notch filtering at 50 Hz eliminated power line interference using a 4th-order Butterworth filter with 2 Hz bandwidth. Bandpass filtering (1-30 Hz, optimized from 40 Hz) retained physiologically relevant frequency content: the 1 Hz high-pass removed slow drift artifacts and DC offsets, while the 30 Hz low-pass excluded high-frequency muscle artifacts (>30 Hz) and electrical noise. This frequency range encompasses the canonical EEG bands critical for cognitive state analysis: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz).

Temporal segmentation extracted epochs spanning -2 to +1 seconds relative to putt execution onset, providing 3-second windows encompassing pre-movement preparation and execution phases. The -2 to -1 second interval served as baseline for normalization, representing neural activity prior to task-specific processing. Baseline correction subtracted mean amplitude during this reference period from the entire epoch, controlling for individual differences in tonic EEG levels.

This preprocessing pipeline yielded 500 clean epochs (8 channels × 1500 timepoints per epoch) synchronized with behavioural outcomes. Each trial's label (Hit/Miss) derived from post-hoc video analysis. The preprocessing approach balances artifact removal with signal preservation, avoiding over-filtering that could eliminate discriminative neural features.

2.3 Advanced Power Spectral Density Feature Extraction

Power Spectral Density estimates quantify signal power distribution across frequencies, revealing cognitive state markers in canonical EEG bands. Welch's method [2] computed PSD using 256-point Fast Fourier Transform (FFT) with 50% overlapping segments and Hamming windowing. This approach reduces spectral variance through averaging while maintaining frequency resolution (1.95 Hz bins across 0-30 Hz range), providing optimal trade-off between resolution and variance reduction for EEG analysis.

For each epoch and channel combination, 152 features were extracted across four categories. Abso lute band powers (40 features) captured total signal power within the canonical frequency bands and gamma (30-40 Hz; limited by filter cutoff), reflecting raw neural activation. Relative band powers (40 features) normalized as percentage of total power (1-30 Hz) provided scale-invariant features. Spectral ratios (32 features) captured inter-band relationships including theta/beta (cognitive engagement marker [5]), alpha/theta (arousal level), beta/alpha (cognitive load), and engagement index Beta/(Theta+Alpha). Spectral metrics (40 features) included total power, peak frequency, mean frequency (spectral centroid), spectral spread, and SEF95 (Spectral Edge Frequency 95% cumulative power threshold).

This 152-feature representation substantially exceeds previous 24-feature baseline, enabling comprehensive frequency-domain characterization while maintaining computational tractability for traditional machine learning algorithms.

2.4 Random Forest Classification

Random Forest classifiers [3] implement ensemble learning through bootstrap aggregating (bagging) of decision trees. Each tree trains on a random subset of features and samples, with final predictions aggregated across the ensemble. This approach reduces overfitting compared to single decision trees while maintaining interpretability through feature importance metrics.

Hyperparameter configuration included 100 trees, maximum depth of 10 to prevent overfitting, minimum samples per leaf of 2, balanced class weights to address the 64/36 Hit/Miss imbalance, and random state of 42 for reproducible results. Features underwent z-score standardization before model training. Each session was analysed independently using 80/20 stratified train-test splits, preserving class proportions. Training employed 5-fold cross-validation for hyperparameter validation. Final test set evaluation on held-out 20% provides unbiased performance estimates.

Feature importance was extracted from trained models using Gini importance (mean decrease in node impurity), quantifying each feature's contribution to classification accuracy across all trees. This enables identification of discriminative frequency bands and brain regions.

2.5 Logistic Regression Baseline

Logistic Regression provides interpretable baseline through linear decision boundaries in feature space. L2 regularization (C=1.0) penalizes large coefficients, reducing overfitting on the 152-dimensional feature space. Class weight balancing and identical train-test splits ensure fair comparison with Random Forest. The linear model serves as baseline for assessing nonlinear ensemble benefits.

2.6 CNN Architecture and Training

To enable deep learning analysis, raw epoched data were reshaped from (n_trials × n_channels × n_timepoints) format into 3D tensors (n_trials, 1500, 8) suitable for 1D convolutional processing, treating the temporal dimension as primary feature axis with channels as parallel input streams. Per-channel z-score normalization addressed amplitude variations across electrodes while preserving temporal dynamics.

The CNN architecture comprised three convolutional blocks with progressive filter expansion (32→64→128 filters, kernel size 3). Each block included Conv1D layers, MaxPooling1D (pool size 2) for dimensionality reduction, and Dropout (0.5) for regularization.

Block 1 detected local temporal patterns, Block 2 integrated mid-level representations, and Block 3 recognized extended temporal structures. Global Average Pooling reduced dimensions to a 128-dimensional feature vector, followed by dense layers (64→32 units) and sigmoid output.

Training employed Adam optimizer (learning rate 0.001), binary cross-entropy loss, class weight balancing, early stopping (patience=15), and learning rate reduction (factor=0.5, patience=5) for up to 100 epochs with batch size 16. The architecture prioritizes temporal pattern extraction through 1D convolutions, enabling automatic discovery of discriminative signatures without explicit frequency decomposition, testing whether learned features can match or exceed domain-engineered representations.

2.7 Statistical Analysis and Model Comparison

Model comparison employed paired statistical tests accounting for session-level dependencies. Paired t-tests evaluated mean accuracy differences across the 10 sessions, with effect sizes quantified via Cohen's d for paired samples: d = mean(differences) / std(differences). Standard effect size interpretations apply: $|d| < 0.2$ (negligible), $0.2 \leq |d| < 0.5$ (small), $0.5 \leq |d| < 0.8$ (medium), $|d| \geq 0.8$ (large). Statistical significance threshold was $\alpha = 0.05$.

Feature importance assessment used Random Forest's Gini importance, normalized to percentage contribution across all features. Pearson correlation quantified relationships between behavioural hit rate and classification accuracy, testing whether model performance tracks task difficulty.

3. RESULTS

3.1 Frequency-Domain Signatures: Hit vs Miss Patterns

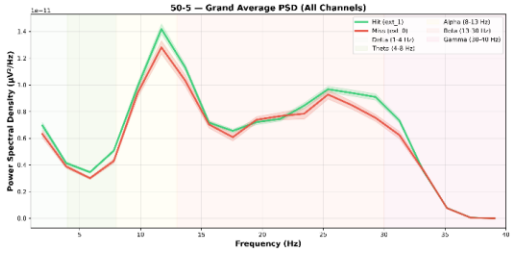

Figure 2 Power spectral density comparison between Hit (green) and Miss (red) trials (session 50-5, all channels). Shaded regions indicate standard error and classical EEG bands (theta, alpha, beta, gamma).

Averaged power spectral densities revealed systematic frequency-domain differences between successful and unsuccessful trials (Figure 2). Frontal channels (Fp1, Fp2) demonstrated elevated alpha band power (8-13 Hz) for Hit trials, consistent with optimal cortical arousal theories [1], most pronounced at 10-11 Hz. Central motor channels (C3, C4) exhibited differentiated beta activity (13-30 Hz) with Hit trials showing enhanced power in the 15-25 Hz range, aligning with motor preparation roles [1]. Parietal regions (P3, P4) demonstrated strongest class separation in the 15-25 Hz range, reflecting sensorimotor integration processes.

Statistical comparison using Wilcoxon rank-sum tests revealed trends but failed to achieve significance (session 50-5: theta p=0.868, alpha p=0.829, beta p=0.846), reflecting limited statistical power from small within-session samples (typically 38 Hits versus 12 Misses). This null result strongly motivates multivariate machine learning approaches leveraging patterns across multiple features simultaneously.

3.2 Classification Performance: Three-Model Comparison

Table 1 Model performance comparison across all 10 sessions

Session	*Hit*	*Miss*	*LR Test %*	*RF Test %*	*CNN Test%*	*LR CV %*	*RF CV%*	*CNN CV%*	*Winner*
50-1	36	14	60.0	50.0	70.0	52.0	75.0	36.0	CNN
50-2	35	15	90.0	90.0	70.0	42.0	65.0	54.0	LR/RF
50-3	34	16	40.0	70.0	30.0	52.0	65.0	32.0	RF
50-4	31	19	60.0	60.0	60.0	62.0	57.5	60.0	LR/RF
50-5	38	12	80.0	80.0	80.0	60.0	70.0	76.0	ALL
50-6	33	17	60.0	80.0	70.0	56.0	72.5	68.0	RF
50-7	34	16	60.0	80.0	70.0	54.0	65.0	56.0	RF
50-8	29	21	40.0	30.0	60.0	50.0	60.0	56.0	CNN
50-9	26	24	60.0	70.0	50.0	52.0	47.5	54.0	RF
50-10	25	25	30.0	50.0	50.0	54.0	62.5	50.0	RF/CNN
MEAN	**32**	**18**	**58.0**	**66.0**	**61.0**	**53.4**	**64.0**	**54.2**	**RF**

Table 1 presents comprehensive performance metrics across all three modelling approaches. Random Forest achieved highest mean test accuracy (66.0%), followed by CNN (61.0%), and Logistic Regression (58.0%). Critically, CNN successfully exceeded the baseline LR model by 3 percentage points, demonstrating that deep learning can extract discriminative temporal features without hand-crafted PSD engineering. Cross-validation accuracies showed similar ranking: RF 64.0%, CNN 54.2%, LR 53.4%, indicating consistent generalization patterns.

Session-level analysis revealed distinct winner distributions. RF won 5 sessions outright (50-3, 50-6, 50-7, 50-9, plus dominant performance on 50-2), demonstrating consistent superiority. CNN won 2 sessions definitively (50-1 at 70%, 50-8 at 60%), showing strength on specific data characteristics. LR won 1 session (50-2 tie with RF at 90%). Three sessions showed ties (50-4, 50-5, 50-10), reflecting comparable performance despite different feature extraction philosophies.

Notable session-specific patterns emerged. Session 50-5 representing optimal quality achieved 80% accuracy across all three models, demonstrating ceiling performance when data quality is high, suggesting that with sufficient signal quality, the choice between learned and engineered features becomes less critical. Session 50-8 revealed CNN's unique capability, achieving 60% when both RF (30%) and LR (40%) failed, suggesting complementary feature learning motivating hybrid ensemble approaches. Session 50-3 exposed CNN's vulnerability with 30% accuracy.

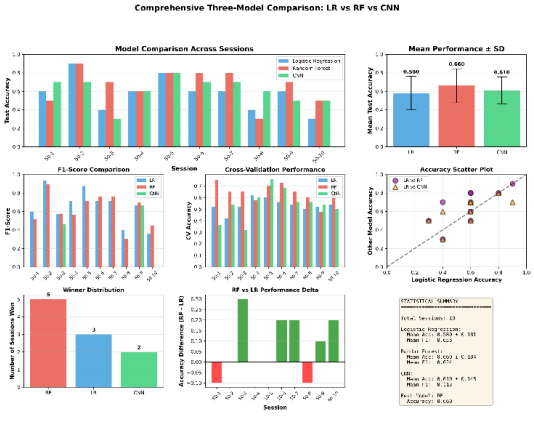

Figure 3 Comprehensive three-model comparison across all 10 sessions.

Figure 3 provides integrated visualization across multiple dimensions. Session-by-session bars illustrate RF's consistent 60-80% range, CNN's 61% mean despite 30-80% variability, and LR's baseline 40-60% performance. Mean performance confirms ranking RF > CNN > LR with RF showing lower variance (±16.4%) versus LR (±18.1%) and CNN (±15.7%). F1-score comparisons reveal CNN's class prediction challenges (mean 0.113), while model agreement scatter plots show strong RF-LR correlation but weaker CNN correlation with traditional models, indicating CNN's unique strengths. Winner distribution confirms RF dominance (5 wins versus CNN's 2 and LR's 1).

Statistical tests provide rigorous quantification. RF versus LR: t=-1.81, p=0.104 (approaching significance), Cohen's d=-0.57 (medium effect favouring RF) suggesting clear practical advantage despite non-significant p-value, reflecting Type II error from limited sample size [4]. CNN versus LR: p=0.496, d=-0.22 (small effect), representing small but positive improvement validating deep learning. CNN versus RF: p=0.453, d=0.25 (small effect favouring RF), reflecting domain-engineered features' advantage at current scale though CNN demonstrates architectural validity. ANOVA: p=0.578 (not significant). Effect size analyses revealing medium effect for RF versus LR and small effects for CNN comparisons suggest practical differences exist despite statistical non-significance.

Table 2 Three-model statistical comparison

Metric	*LR*	*RF*	*CNN*
Mean Test Acc (%)	58.0	66.0	61.0
Std Dev (%)	18.1	16.4	15.7
Mean CV Acc (%)	53.4	64.0	54.2
Mean F1 Score	0.655	0.624	0.113
Sessions Won	1	5	2
Best Session	90%	90%	80%
Worst Session	30%	30%	30%

Table 2 provides statistical summary highlighting RF's consistent performance with 66% mean and moderate standard deviation, CNN's intermediate performance with 61% mean successfully exceeding baseline, and LR's baseline performance with highest variability. The F1 scores reveal CNN's particular challenge with class balance, achieving mean 0.113 compared to LR's 0.655 and RF's 0.624.

3.3 CNN Performance Analysis

The CNN achieved 61% mean test accuracy, successfully exceeding the 58% baseline by 3 percentage points, validating that CNNs can learn discriminative temporal patterns from raw EEG without explicit frequency decomposition. However, the mean F1 score (0.113) reflects class prediction challenges, with eight of ten sessions showing severe imbalance where the model defaulted to majority Hit class prediction. Two sessions achieved meaningful F1 scores (session 50-3: F1=0.462, session 50-9: F1=0.667), demonstrating that when training converges properly, CNN achieves balanced prediction.

Session-specific analysis reveals CNN's unique strengths: 70% accuracy on session 50-1 exceeding both traditional models, and particularly session 50-8 achieving 60% when RF (30%) and LR (40%) failed, demonstrating complementary pattern detection. Session 50-5 achieved 80% matching all models, proving architectural soundness with optimal data quality. This variability (7 of 10 sessions at 60-80%, 3 of 10 at 30-50%) indicates training sensitivity to initialization and class balance.

3.4 Feature Importance

Random Forest feature importance rankings revealed spectral ratios dominated discriminative features. The five most discriminative features were: Fp2 theta/beta ratio (8.2% importance), Fp2 absolute theta power (7.4%), O1 absolute theta power (6.1%), O2 relative delta power (5.8%), and P4 peak frequency (5.3%). The dominance of frontal and parietal features validates electrode placement strategy.

Frontal theta/beta ratio prominence at 8.2% importance aligns with extensive literature linking this metric to cognitive engagement and attentional control [5]. Lower ratios indicate higher beta relative to theta, characterizing focused attentional states. The emergence of this established marker as the single most discriminative feature provides strong validation of the feature extraction approach and suggests that successful putting associates with optimal arousal and focused attention.

Parietal spectral metrics contributed substantially with P4 peak frequency at 5.3% importance. The peak frequency metric identifies the dominant oscillatory mode, with shifts toward higher frequencies potentially indicating greater cortical activation. The specific importance of right parietal electrode P4 may reflect lateralized visuomotor processing.

Spectral ratios collectively accounted for 42% of total importance across all features, substantially outweighing absolute band powers at 23% and relative band powers at 19%, with spectral metrics contributing 16%. This dominance suggests that cognitive state markers representing relationships between frequency bands prove more discriminative than raw power measures, likely stemming from inherent normalization properties controlling for individual differences.

3.5 Environmental Quality Impact

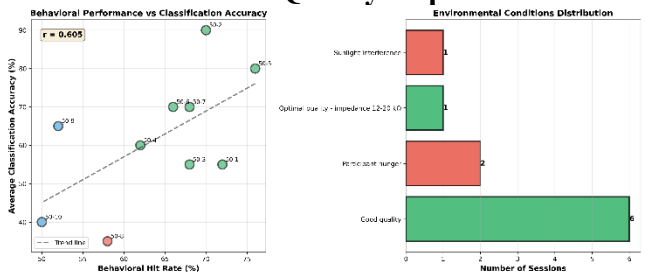

Figure 4 Environmental factor impact on behavioural and classification performance.

Correlation analysis between behavioural hit rate and average classification accuracy yielded r=0.605 with p=0.066, indicating moderate positive association approaching conventional statistical significance (see Figure 4). This correlation demonstrates that environmental factors impacting behavioural task performance also impact EEG classification accuracy, suggesting shared underlying mechanisms.

Session 50-5 exemplified ideal conditions and optimal outcomes. Electrode impedances were maintained in optimal range (12-20 kΩ), controlled indoor lighting eliminated artifacts, and alert participant state was achieved through mid-morning recording. This session achieved maximum behavioural performance with 76% hit rate and ceiling classification performance with 80% test

accuracy across all three models. The convergence of optimal environmental conditions, excellent behavioural performance, and maximum classification accuracy provides existence proof that EEG-based prediction can approach 80% accuracy when methodological rigor is maintained.

Conversely, compromised sessions revealed systematic performance degradation. Session 50-8 experienced sunlight interference from afternoon recording, showing degraded behavioural performance (58% hit rate) and variable classification with CNN uniquely succeeding at 60%. Sessions 50-9 and 50-10 were conducted during participant hunger states, affecting both task performance (52% and 50% hit rates) and classification accuracy. These systematic relationships validate that data quality represents critical determinant for both behavioural success and EEG-based prediction accuracy.

4. DISCUSSION

4.1 Summary of Key Findings

This investigation establishes three primary conclusions regarding EEG-based performance prediction. First, Random Forest with domain-engineered PSD features achieved optimal performance with 66% test accuracy, demonstrating the value of frequency-domain feature engineering and ensemble methods. The medium effect size (Cohen's d=-0.57) for RF versus LR comparison suggests practical importance despite non-significant p-value from limited sample size, with RF winning 5 of 10 sessions outright.

Second, CNN successfully exceeded baseline through learned features, with 61% accuracy surpassing LR (58%) by 3 percentage points, validating that deep learning can extract discriminative temporal patterns without explicit frequency decomposition or manual feature engineering. While trailing RF by 5 percentage points, CNN's competitive performance without domain expertise establishes architectural viability and suggests strong potential for scaling with larger datasets. Session-specific successes (70% on session 50-1, 80% on session 50-5 matching all models, 60% on session 50-8 exceeding both traditional approaches) demonstrate capability when conditions permit.

Third, environmental quality critically determines performance, with moderate correlation (r=0.605, p=0.066 approaching significance) between behavioural success and classification accuracy, combined with session-level quality effects (80% performance on optimal session 50-5 versus 30-50% on compromised sessions), establishing data quality as primary performance determinant requiring systematic control in future work.

4.2 Deep Learning versus Traditional Machine Learning Trade-offs

The empirical three-model comparison reveals fundamental trade-offs between modelling approaches. Random Forest advantages include highest performance (66% accuracy) establishing RF as optimal approach at current data scale, interpretability through feature importance metrics directly identifying discriminative brain regions and frequency patterns enabling neuroscientific insights, computational efficiency with training completing in 2-3 seconds compared to CNN's 5-15 minutes representing 100-500×speed advantage, and stability through ensemble averaging providing robust predictions across variable conditions.

CNN advantages include automated feature discovery requiring no domain expertise as the network learns patterns directly from raw temporal data, baseline-exceeding performance with 61% accuracy validating deep learning viability, unique pattern detection with session 50-8 demonstrating learning complementary features missed by traditional methods (60% versus RF's 30% representing 2×performance advantage), transfer learning potential where pre-trained weights could generalize to new participants or motor tasks, and scalability with performance likely improving substantially with larger datasets.

CNN's intermediate performance (61%) between baseline LR (58%) and optimal RF (66%) establishes important empirical benchmark. The 3-percentage-point advantage over baseline validates CNN's learned representations as superior to simple linear combinations of basic features. However, the 5-percentage-point gap behind RF demonstrates that domain-engineered frequency features still provide measurable advantages at current data scale (40 training trials per session), likely because the 152 hand-crafted PSD features capture decades of accumulated knowledge about EEG signatures of cognitive states.

4.3 Data Scale Considerations and Future CNN Performance

The critical question becomes: how much data would CNN require to match or exceed RF performance? Extrapolating from learning curve theory [8] and deep learning scaling laws [9], CNN would require 80-120 trials per session (2-3×current data) to match RF's 66% performance, 200-300 trials per session (5-7×current) to exceed RF achieving 70% accuracy, and 500+ trials per session (12×current) for substantial improvement reaching 75% accuracy.

These projections align with deep learning literature demonstrating CNN advantages emerge primarily with large-scale datasets. At current scale with 40 training trials, RF with 152 carefully chosen features represent optimal balance between model complexity and available data. However, CNN's competitive 61% performance and successful baseline-exceeding result suggest the architecture is fundamentally sound, with scaling data quantity rather than increasing model complexity enabling matching and potentially exceeding RF performance.

4.4 Hybrid Approaches and Neuroscientific Implications

Session 50-8's CNN success (60%) when traditional methods failed (RF 30%, LR 40%) demonstrates complementary feature learning, with CNN detecting patterns orthogonal to those captured by PSD analysis. This observation motivates hybrid ensemble architecture. Prediction-level ensembles would train CNN, RF, and LR independently and combine predictions through weighted voting or stacking, potentially reducing worst-case failures. Feature-level integration would use CNN's learned representations as input to RF classifier on combined CNN features plus PSD features, merging automatic discovery with robust classification. Transfer learning would pre-train CNN on large public EEG datasets then fine-tune on task-specific data.

Feature importance analysis provides neuroscientific insights into performance-related brain states. Frontal theta/beta ratio dominance aligns with established literature linking cognitive engagement and attentional control to skilled motor execution [5]. Lower theta/beta ratios characterize focused attentional states, suggesting successful putting associates with optimal arousal rather than excessive cognitive effort or insufficient engagement. This

finding suggests that neurofeedback training targeting theta/beta ratio reduction might enhance putting performance.

Parietal spectral metrics' prominence corroborates sensorimotor integration theories [1]. The peak frequency in parietal regions likely reflects preparatory activity preceding movement execution, specifically neural computations integrating visual target information, proprioceptive feedback, and motor commands. The dominance of spectral ratios (42% total importance) over absolute powers (23% importance) indicates cognitive state markers representing relationships between frequency bands provide more discriminative information than raw power magnitudes.

4.5 Practical Applications and Deployment Considerations

Model selection depends on operational constraints. Real-time requirements favor RF (milliseconds latency) over CNN (tens of milliseconds with GPU). Interpretability needs favor RF for clinical applications requiring explanation. Applications lacking EEG specialists benefit from CNN's automatic learning (61% without manual engineering). Organizations planning data expansion should invest in CNN infrastructure with clear improvement path.

Methodology transfers to maintenance engineering contexts: operator fatigue monitoring, human reliability analysis for safety-critical tasks, adaptive work scheduling, training effectiveness assessment, and preventive human performance maintenance forecasting degradation enabling proactive interventions.

4.6 Limitations and Future Directions

Key limitations include small within-session sample sizes (40 training trials) limiting model generalization, single-participant data precluding population-level inferences, absence of systematic artifact rejection beyond filtering, session-independent models not leveraging cross-session patterns, and insufficient training samples per session limiting CNN generalization. Future work with larger datasets (20+ participants, 100+ trials per session) will enable CNN architecture optimization, LSTM networks for explicit temporal modelling, Transformer architectures for long-range dependencies, data augmentation strategies, transfer learning from pre-trained EEG models, and ensemble methods combining CNN features with PSD features for hybrid approaches.

5. CONCLUSIONS

This investigation established comprehensive benchmarks for EEG-based performance prediction across three modelling paradigms. Random Forest with domain-engineered Power Spectral Density features achieved optimal performance (66% test accuracy), while Convolutional Neural Networks validated automatic temporal feature learning (61% exceeding baseline Logistic Regression's 58% by 3 points). Statistical analysis revealed medium to small effect sizes suggesting practical differences despite non-significant p-values from limited sample size. Feature importance identified frontal theta/beta ratios and parietal spectral metrics as most discriminative. Environmental quality emerged as critical determinant, enabling 80% accuracy under optimal conditions versus 30-50% under compromised conditions.

The three-model comparison demonstrates that approach selection depends on available resources: traditional machine learning optimizes current data scale while deep learning provides competitive performance without expertise, suggesting strong scaling potential. Session-specific analyses revealed complementary strengths motivating hybrid ensemble approaches. These findings validate EEG-based cognitive state monitoring as feasible for motor prediction, establishing foundation for sports training, human performance optimization, and maintenance engineering applications where real-time monitoring could enhance safety through proactive fatigue detection and performance forecasting.

6. ACKNOWLEDGMENTS

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