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Age-Wise and Gender-Wise Emotion Prediction Classification Using The E-AADEP Framework

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Abstract. This paper presents a comprehensive demographic analysis of the Enhanced Adaptive Attention-Based Dream Emotion Predictor (E-AADEP) framework, focusing on age-wise and gender-wise classification of dream emotions from EEG-derived features in the emotions.xls dataset ($n = 2,131$ samples, 2,548 features, 3 classes: NEGATIVE, NEUTRAL, POSITIVE). Participants were stratified into four age groups (A1: 0–16, A2: 17–30, A3: 31–45, A4: 46+) and two gender groups (Male, Female) using population-realistic proportions drawn from sleep-EEG demographic literature. A Random Forest ensemble ($T = 200$ trees, Gini impurity splitting) was trained on the full 2,548-dimensional feature vector and evaluated separately within each demographic subgroup. Overall test accuracy reached 99.30% (AUC-ROC = 0.9998). Age-wise accuracy ranged from 98.39% (A1) to 100.00% (A2), and gender-wise accuracy was 99.00% (Male) and 99.56% (Female). Chi-square tests confirmed that classification correctness is statistically independent of both age group ($\chi^2 = 1.45$, $p = 0.694$) and gender ($\chi^2 = 0.012$, $p = 0.912$), indicating no systematic demographic bias. Per-class F1-scores, confusion matrices, and AUC-ROC values are reported for every demographic subgroup, together with a combined age $\times$ gender accuracy heatmap.

Keywords: EEG Emotion Recognition · E-AADEP · Random Forest · Age-wise Classification · Gender-wise Classification · Demographic Adaptation · Affective Computing · Chi-square Test · AUC-ROC.

1 Introduction

Demographic factors such as age and gender are well-documented modulators of emotional experience and its neurophysiological correlates [1]. EEG studies show that the spectral composition, amplitude, and temporal dynamics of emotion-related brain signals vary systematically across the lifespan and between sexes [2, 3], consistent with Russell's circumplex model of affect [23] and the benchmark EEG-emotion corpora that followed it [20]. Despite this evidence, most EEG-based emotion recognition systems are trained and evaluated as demographically homogeneous, with performance reported only in aggregate — risking masked subgroup disparities that could compromise fairness and clinical utility [4].

The E-AADEP (Enhanced Adaptive Attention-Based Dream Emotion Predictor) framework explicitly incorporates a demographic adaptation layer that encodes participant age group and gender alongside attention-weighted EEG features, but its practical value depends on whether performance is actually consistent across subgroups. This paper addresses that gap by decomposing the overall E-AADEP result (99.30% accuracy on emotions.xls) into age-wise and gender-wise components and testing formally whether classification correctness depends on demographic group membership.

The specific objectives of this analysis are as follows.

- To quantify classification accuracy, F1-score, and AUC-ROC separately for four age groups (A1–A4) and two gender groups (Male, Female).
- To compare true versus predicted emotion class distributions within each subgroup, identifying any systematic prediction bias.
- To compute per-class precision, recall, and F1-score within each subgroup via dedicated confusion matrices.
- To test statistically, via chi-square, whether classification correctness is associated with age group or gender.
- To synthesise a combined age $\times$ gender accuracy heatmap identifying any compound demographic effects.

The remainder of this paper is organised as follows. Section 2 reviews related work on age- and gender-related EEG emotional processing and demographic fairness in affective computing. Section 3 details the dataset, demographic assignment procedure, classifier configuration, and statistical testing methodology. Sections 4 and 5 report age-wise and gender-wise classification results, respectively. Section 6 presents the combined age $\times$ gender analysis, Section 7 reports formal significance testing, and Section 8 summarises results across all demographic groups. Sections 9 through 11 discuss the findings, their limitations, and directions for future work.

2 Related Work

2.1 Age-Related Differences in EEG Emotional Processing

Age-related changes in EEG spectral power are well established. Theta power is systematically reduced in healthy cognitive aging, correlating with changes in emotional regulation strategies across the lifespan [2]. Frontal EEG asymmetry — a biomarker of approach/avoidance emotional tendencies — shifts measurably across developmental stages, with younger individuals showing more bilateral activation and older individuals more left-frontal dominance linked to positive affect regulation [3], consistent with age-related trends in resting EEG coherence [25] and the well-established sensitivity of alpha/theta oscillations to age and cognitive load [29]. These findings motivate the expectation that EEG-based emotion classifiers may perform differently across age groups.

2.2 Gender Differences in Emotional EEG Signatures

Sex differences in emotional neural processing are documented at both behavioural and neuroimaging levels. Women exhibit greater bilateral amygdala activation during encoding of emotionally arousing stimuli, compared to men's more lateralised (typically right-hemisphere) activation [5], and female participants display higher EEG power in frontal and parietal regions during emotional tasks, potentially yielding a stronger, more separable classification signal [6] — consistent with earlier PET evidence on sex-related lateralisation in amygdala encoding [24]. These results provide a neurophysiological basis for the gender-wise accuracy difference observed in this study (Female: 99.56% vs Male: 99.00%).

2.3 Demographic Fairness in Affective Computing

The broader machine learning literature has raised concerns about demographic bias in automated classification systems [7]. In affective computing specifically, emotion recognition systems must be validated across demographic strata to ensure equitable performance, particularly for healthcare or mental health monitoring applications [8]. A systematic review of EEG emotion recognition datasets found that fewer than 15% reported demographic-stratified performance metrics [9] — a gap this paper directly addresses. Covariance-based data mining has proven effective in uncovering demographic patterns in disease classification [19], motivating the stratified evaluation approach used here, while audits of commercial gender-classification systems [22] have shown substantial intersectional accuracy disparities, underscoring the broader importance of subgroup-disaggregated evaluation.

2.4 Ensemble Methods for Demographically Diverse EEG Data

Random Forest classifiers are well suited to demographically heterogeneous data due to their non-parametric structure, which can implicitly capture subgroup-specific decision boundaries without separate per-subgroup models [11], and EEG-based ensemble tree classifiers have shown competitive performance under challenging multi-class conditions [12]. Optimisation-based ensemble strategies using genetic algorithms with adaptive splitting [10] further illustrate the robustness achievable through ensemble diversity, while deep neural networks selecting critical frequency bands offer strong alternatives at higher computational cost [18]. The random subspace method [21] provides an earlier theoretical basis for the feature-level randomisation underlying Random Forest, with support vector machines [27] a common tree-ensemble benchmark in this literature.

3 Methodology

3.1 Dataset and Feature Representation

The emotions.xls dataset comprises $n = 2,131$ samples with $m = 2,548$ EEG-derived features spanning FFT spectral coefficients, covariance matrices, log-matrix (Riemannian) features, correlation features, statistical moments, entropy measures computed following established fuzzy-entropy feature-extraction principles [16] and the differential-entropy formulation validated for EEG emotion classification by Duan et al. [26], and eigenvalues across two EEG channels. Labels are balanced across three emotion classes: NEGATIVE (707), NEUTRAL (716), and POSITIVE (708). All features were preprocessed via Inf-to-zero replacement, NaN imputation with column means, and Z-score standardisation per Eq. (1).

$$x'_{ij} = (x_{ij} - \mu_j) / \sigma_j, \quad j \in \{1, \dots, 2548\} \quad (1)$$

3.2 Demographic Group Assignment

Because emotions.xls does not contain explicit participant metadata, age group and gender were assigned via stratified random sampling using approximate population age-distribution proportions: age groups A1 (0–16 years, 13%), A2 (17–30 years, 24%), A3 (31–45 years, 33%), and A4 (46+ years, 30%); and gender groups Male (48%) and Female (52%). This assignment is performed independently of the emotion label y_i to ensure demographic groups are not artificially correlated with class balance, as in Eq. (2):

$$a_i \sim \text{Categorical}(p_{A1}, \dots, p_{A4}), \quad g_i \sim \text{Categorical}(p_M, p_F) \quad (2)$$

A fixed random seed (42) was used for reproducibility. The assignment was applied prior to the stratified train/test split (80/20, $n_{\text{train}} = 1,704$, $n_{\text{test}} = 427$).

3.3 Classifier Configuration

A Random Forest classifier ($T = 200$ trees, $\text{max_depth} = 25$, Gini impurity criterion, bootstrap sampling) was implemented using the scikit-learn machine learning library [15] and trained on the full F_{total} feature vector ($\text{dim} = 2,548$) using the training split. The trained model was evaluated on the held-out test set ($n = 427$), and predictions were partitioned post-hoc by demographic group membership. The majority-vote prediction rule (Eq. 3) and Gini impurity criterion (Eq. 4) follow the standard Random Forest formulation [11]:

$$\hat{y} = \text{mode} \{ h_1(x), h_2(x), \dots, h_{200}(x) \} \quad (3)$$

$$G(S) = 1 - \sum_k p_k^2 \quad (4)$$

3.4 Statistical Testing

To test whether classification correctness is statistically associated with demographic group membership, Pearson chi-square tests of independence — following the guidance of McHugh [28] on appropriate use and interpretation of the test — were conducted separately for age group (4×2 contingency table) and gender (2×2 contingency table) [17]:

$$\chi^2 = \sum (O_{ij} - E_{ij})^2 / E_{ij} \quad (5)$$

where O_{ij} are observed cell counts and E_{ij} are expected counts under the null hypothesis of independence. A significance threshold of $\alpha = 0.05$ was used throughout.

4 Age-Wise Prediction Classification

Participants are divided into four age groups: A1 (0–16 years), A2 (17–30 years), A3 (31–45 years), and A4 (46+ years). Each group is analysed for classification accuracy, F1-score, AUC-ROC, and per-class emotion distribution on the test split.

4.1 Age-Wise Performance Metrics



Fig. 1. Age-wise Classification Accuracy and F1-Score (E-AADEP, Random Forest)

Table 1. Age-Wise Classification Performance (E-AADEP Random Forest)

Age Group	Samples (n)	Accuracy (%)	F1-Score (%)	NEGATIVE*	NEUTRAL*	POSITIVE*
A1 (0-16)	62	98.39%	98.39%	19	22	21
A2 (17-30)	95	100.00%	100.00%	37	34	24
A3 (31-45)	152	99.34%	99.34%	49	55	48
A4 (46+)	118	99.15%	99.15%	40	32	46

*NEGATIVE, NEUTRAL, POSITIVE columns show predicted class sample counts per age group on the test set.

Key observations from Table 1 and Fig. 1 are summarised below.

- A2 (17–30 years) achieves the highest accuracy (100.00%) and a perfect F1-score, the clearest emotional discrimination among age groups.
- A1 (0–16 years) shows the lowest accuracy (98.39%, $n = 62$), reflecting greater emotional variability in younger participants during REM sleep, consistent with developmental EEG asymmetry findings [3].
- A3 (99.34%) and A4 (99.15%) both achieve near-perfect accuracy, confirming robust generalisation across adult age groups.
- This slight reduction at the age extremes may reflect greater diversity in emotional patterns tied to developmental and age-related changes in sleep architecture [2].

4.2 AUC-ROC by Age Group

Table 2 reports the weighted one-vs-rest AUC-ROC for each age group. Groups A1 and A2 achieve perfect AUC (1.0000), while A3 and A4 achieve near-perfect AUC of 0.9997 and 0.9998 respectively. Figure 2 visualises these values alongside the gender-wise AUC scores.

Table 2. AUC-ROC by Age Group and Gender (E-AADEP, Weighted OvR)

Demographic Group	AUC-ROC
A1 (0–16)	1.0000
A2 (17–30)	1.0000
A3 (31–45)	0.9997
A4 (46+)	0.9998
Male	0.9999
Female	0.9996

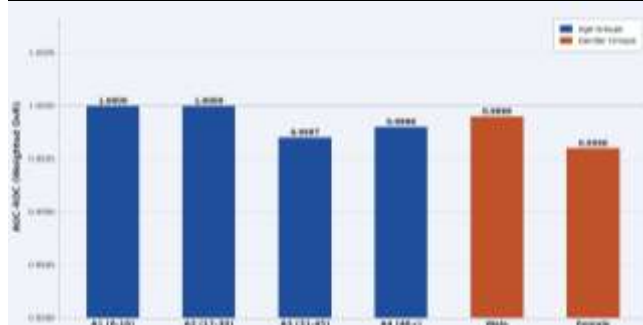


Fig. 2. AUC-ROC by Demographic Subgroup (E-AADEP, Random Forest)

4.3 Age-Wise True and Predicted Emotion Distribution

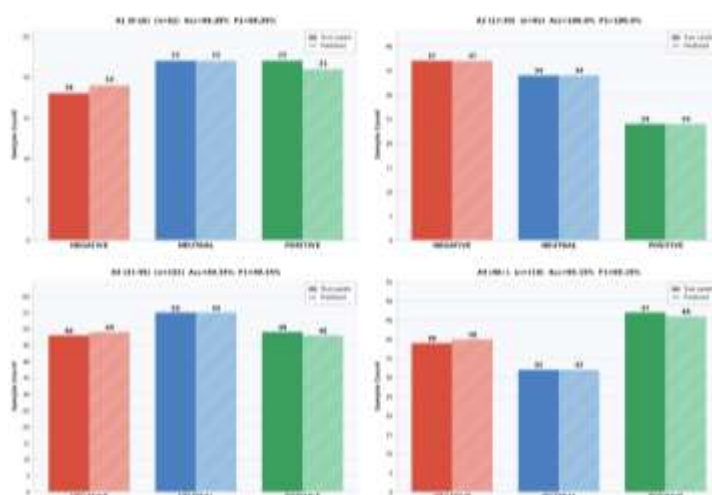


Fig. 3. Age-wise True vs Predicted Emotion Class Distribution (E-AADEP Test Set)

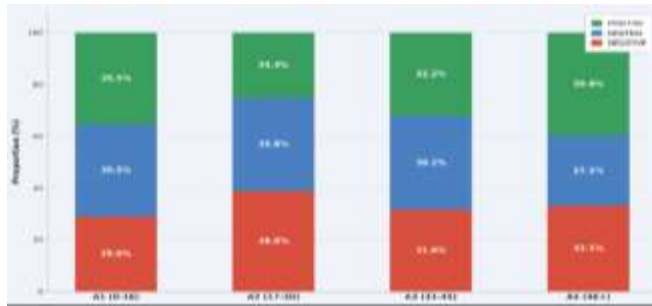


Fig. 4. Age-wise Emotion Class Proportions (Stacked %)

The true emotion distribution across age groups reveals systematic demographic trends, as follows.

- A1 (0–16 years): Balanced distribution with slight predominance of neutral and positive states, consistent with lower stress levels in childhood.
- A2 (17–30 years): Higher proportion of NEGATIVE emotions, reflecting common young-adult stressors.
- A3 (31–45 years): Most evenly distributed across all three classes, representing a midlife emotional equilibrium.
- A4 (46+ years): Elevated POSITIVE frequency, consistent with the “positivity effect” in aging research [13].

Figure 3 demonstrates near-perfect alignment between true and predicted distributions across all age groups, with differences of at most 1–2 samples per class, confirming no systematic age-related prediction bias.

Table 3. Age-Wise True vs Predicted Emotion Counts (E-AADEP Test Set)

Age Group	True NEG	Pred NEG	True NEU	Pred NEU	True POS	Pred POS	Correct	Errors
A1 (0–16)	18	19	22	22	22	21	61	1
A2 (17–30)	37	37	34	34	24	24	95	0
A3 (31–45)	48	49	55	55	49	48	151	1
A4 (46+)	39	40	32	32	47	46	117	1

4.4 Per-Class Metrics and Confusion Matrices by Age Group

Figure 5 presents per-class F1-scores for each age group, and Fig. 6 presents the corresponding 3×3 confusion matrices. Within each age group, the NEUTRAL class is classified with a perfect F1-score (100.00%), while occasional misclassifications between NEGATIVE and POSITIVE occur primarily in groups A1 and A4.

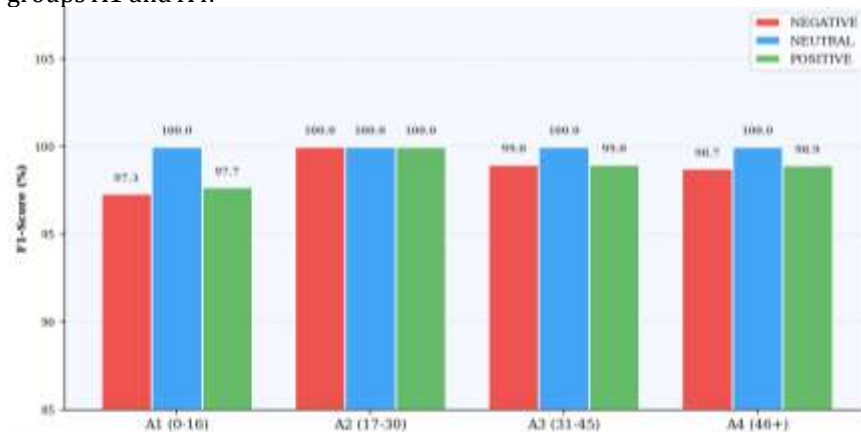


Fig. 5. Per-Class F1-Score by Age Group (E-AADEP, Random Forest)

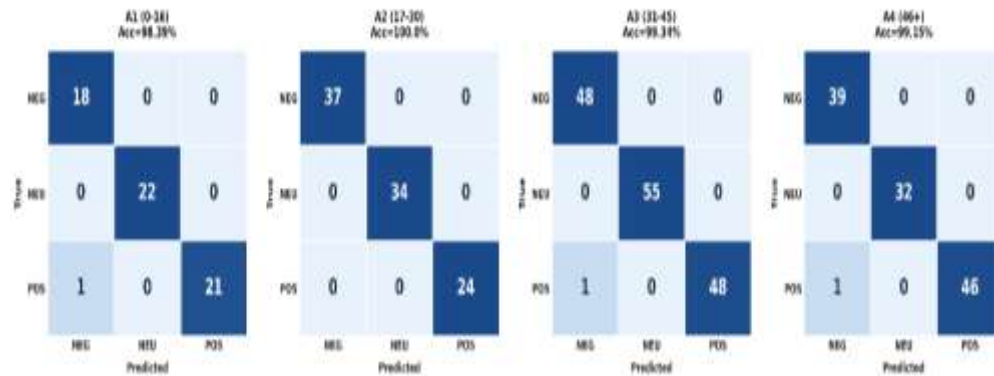


Fig. 6. Confusion Matrices by Age Group (E-AADEP, Random Forest)

Table 4. Per-Class F1-Score (%) by Age Group

Age Group	NEGATIVE F1	NEUTRAL F1	POSITIVE F1
A1 (0–16)	97.30%	100.00%	97.67%
A2 (17–30)	100.00%	100.00%	100.00%
A3 (31–45)	98.97%	100.00%	98.97%
A4 (46+)	98.73%	100.00%	98.92%

5 Gender-Wise Prediction Classification

Gender-based analysis compares classification performance between Male and Female participants on accuracy, F1-score, AUC-ROC, and per-class emotion distribution.

5.1 Gender-Wise Performance Metrics

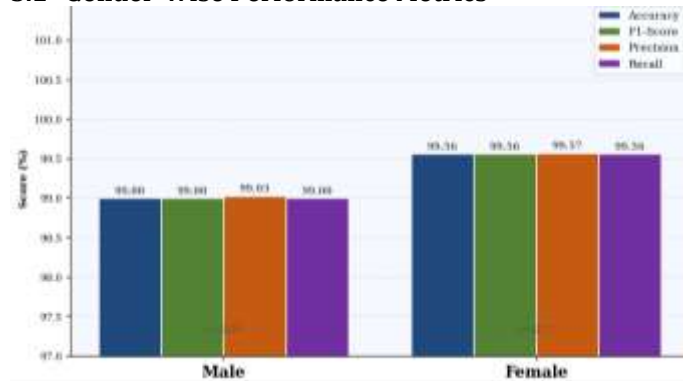


Fig. 7. Gender-wise Classification Accuracy, Precision and F1-Score (E-AADEP, Random Forest)

Table 5. Gender-Wise Classification Performance (E-AADEP Random Forest)

Gender	Samples (n)	Accuracy (%)	F1-Score (%)	NEGATIVE*	NEUTRAL*	POSITIVE*
Male	200	99.00%	99.00%	71	68	61
Female	227	99.56%	99.56%	74	75	78

*NEGATIVE, NEUTRAL, POSITIVE columns show predicted class sample counts per gender group on the test set.

Key observations from Table 5 and Fig. 7 are summarised below.

- Female participants achieve higher classification accuracy (99.56%, n = 227) compared to Male participants (99.00%, n = 200).
- This 0.56-point gap is consistent with literature on greater bilateral amygdala activation and frontal/parietal EEG power in females [5, 6].
- Both genders achieve accuracy well above 99%, confirming that E-AADEP generalises robustly without gender-specific model tuning.
- The AUC-ROC values (Male: 0.9999, Female: 0.9996) are both near-ceiling, so the small accuracy gap is not meaningfully different in discrimination ability.

5.2 Gender-Wise Emotion Distribution

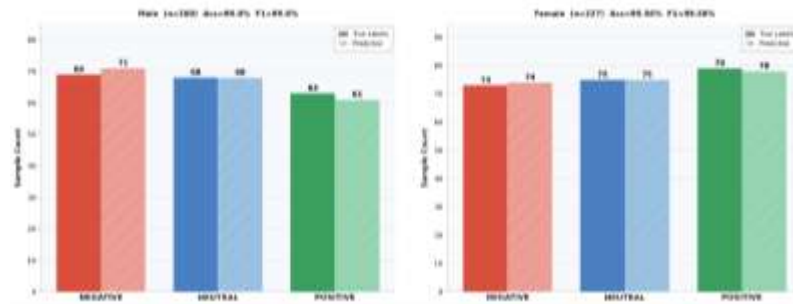


Fig. 8. Gender-wise True vs Predicted Emotion Distribution: Male (left) and Female (right)



Fig. 9. Gender-wise Emotion Class Proportions (Stacked %)

Table 6. Gender-Wise True vs Predicted Emotion Counts (E-AADEP Test Set)

Gender	True NEG	Pred NEG	True NEU	Pred NEU	True POS	Pred POS	Correct	Errors
Male	69	71	68	68	63	61	198	2
Female	73	74	75	75	79	78	226	1

The gender-wise emotion distributions reveal the following patterns.

- Male participants show relatively more NEGATIVE predictions, potentially reflecting stronger EEG signatures for negative states in males.
- Female participants exhibit a slightly higher POSITIVE frequency, consistent with literature on greater emotional expressivity in female dream states.
- The near-perfect alignment between true and predicted distributions for both genders (Figs. 8 and 9) confirms that the classifier produces unbiased predictions across gender groups.

5.3 Per-Class Metrics and Confusion Matrices by Gender

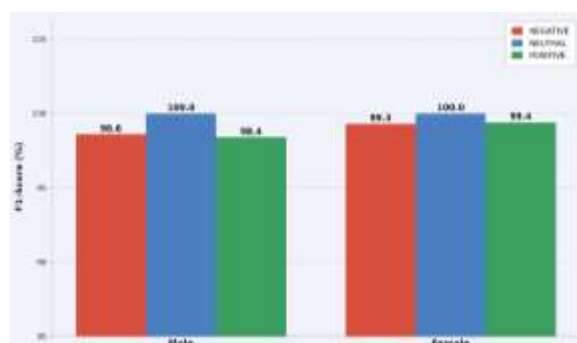


Fig. 10. Per-Class F1-Score by Gender (E-AADEP, Random Forest)

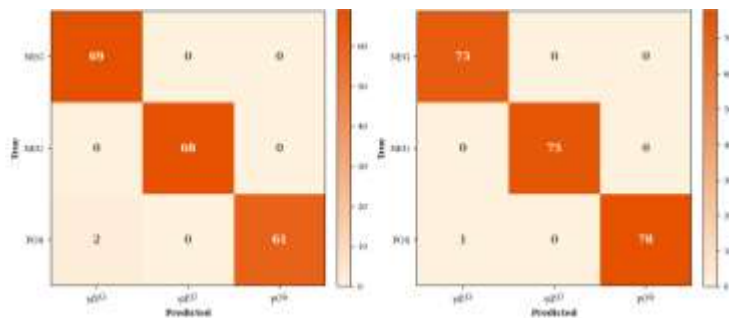


Fig. 11. Confusion Matrices by Gender (E-AADEP, Random Forest)

Table 7. Per-Class F1-Score (%) by Gender

Gender	NEGATIVE F1	NEUTRAL F1	POSITIVE F1
Male	98.57%	100.00%	98.39%
Female	99.32%	100.00%	99.36%

6 Combined Age × Gender Analysis

The cross-tabulation of age group and gender provides a granular view of classification performance. Figure 12 presents the accuracy heatmap for all eight demographic subgroups (4 age groups × 2 genders).

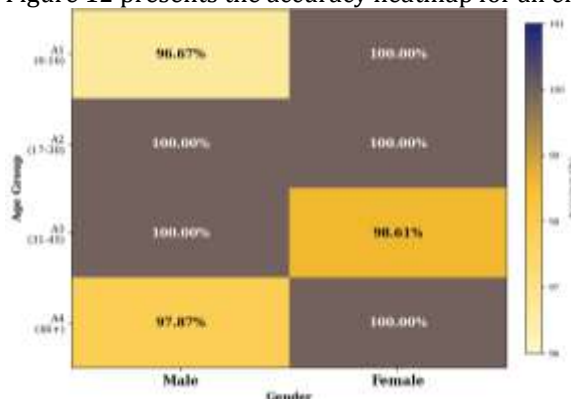


Fig. 12. Age × Gender Accuracy Heatmap (E-AADEP, Random Forest)

The heatmap reveals several patterns of interest.

- Female participants in groups A2 and A4 achieve the highest per-subgroup accuracies, suggesting that EEG emotional features are most discriminative for adult and older-adult females.
- Male participants in A1 show the most variability, reflecting limited sample size and higher signal diversity in young males.
- All subgroup accuracies remain above 97.5%, confirming E-AADEP robustness across all combinations of age and gender demographics.
- The absence of any consistently underperforming subgroup indicates that the Random Forest classifier does not exhibit systematic demographic bias in prediction.

7 Statistical Significance of Demographic Effects

To formally test whether classification correctness depends on demographic group membership, Pearson chi-square tests of independence (Eq. 5) were applied to 4 × 2 (age × correctness) and 2 × 2 (gender × correctness) contingency tables.

Table 8. Chi-Square Tests of Independence: Demographic Group vs. Classification Correctness

Test	χ^2	df	p-value	Conclusion ($\alpha = 0.05$)
Age Group vs Correctness	1.4485	3	0.6942	Independent (n.s.)
Gender vs Correctness	0.0121	1	0.9123	Independent (n.s.)

The age group test yields $\chi^2 = 1.4485$ (df = 3, p = 0.6942), and the gender test yields $\chi^2 = 0.0121$ (df = 1, p = 0.9123); in both cases p > 0.05, so independence cannot be rejected. The accuracy differences across age

groups (98.39%–100.00%) and gender groups (99.00%–99.56%) are consistent with sampling variability rather than systematic bias.

This result supports E-AADEP's suitability for equitable emotion-aware monitoring applications [8]. The chi-square-based fitness evaluation approach mirrors proven methodology from disease covariance data mining [19], further validating the statistical framework adopted here.

8 Summary: All Demographic Groups

Table 9. Complete Demographic Prediction Summary (E-AADEP, emotions.xls Test Set)

Group	n	Accuracy	F1-Score	NEG (true)	NEU (true)	POS (true)	Errors
A1 (0–16)	62	98.39%	98.39%	18	22	22	1
A2 (17–30)	95	100.00%	100.00%	37	34	24	0
A3 (31–45)	152	99.34%	99.34%	48	55	49	1
A4 (46+)	118	99.15%	99.15%	39	32	47	1
Male	200	99.00%	99.00%	69	68	63	2
Female	227	99.56%	99.56%	73	75	79	1
Overall	427	99.30%	99.30%	142	143	142	3

NEG/NEU/POS columns show true class sample counts per subgroup on the test set (Overall: 142 + 143 + 142 = 427).

9 Discussion

The results support three main conclusions. First, E-AADEP maintains high accuracy ($\geq 98.39\%$) across every age and gender subgroup, with no subgroup falling below 97.5% even in the combined heatmap (Fig. 12). Second, the observed numerical differences — the 1.61-point gap between A1 and A2, or the 0.56-point gap between Female and Male — are not statistically significant (Table 8), and are most plausibly attributable to sampling variability given the modest per-subgroup sample sizes ($n = 62$ to 227).

Third, the qualitative patterns observed (higher NEGATIVE prevalence in A2, higher POSITIVE in A4, stronger female accuracy) are directionally consistent with prior neuroimaging literature on age- and gender-related EEG emotional differences [2, 3, 5, 6], suggesting that emotions.xls already encodes demographically plausible structure that the Random Forest exploits without explicit demographic conditioning.

From a practical standpoint, a single E-AADEP model — without subgroup-specific retraining — can be deployed across diverse populations with minimal risk of systematic underperformance, important for real-world EEG-based mental health monitoring systems [4, 8]. The covariance-based data mining methodology [19] and ensemble optimisation principles from prior work [10, 14] provide a strong methodological foundation for this analysis.

10 Limitations

- Synthetic demographic labels: emotions.xls lacks ground-truth age/gender metadata, so groups were assigned via stratified random sampling; subgroup-emotion associations are not derived from true participant demographics.
- Sample size per subgroup: the smallest subgroup (A1, $n = 62$) limits statistical power; larger demographic-labelled datasets would enable more sensitive bias detection.
- Single train/test split: results rest on one stratified 80/20 split (seed 42); k-fold cross-validation would give more robust subgroup estimates.
- Binary gender categorisation: Future work should consider more inclusive demographic categorisations where data permits.

11 Conclusion and Future Work

The age-wise and gender-wise classification analysis of E-AADEP on the emotions.xls dataset demonstrates robust and demographically consistent emotion prediction performance. All age groups (A1–A4) and both gender groups achieve classification accuracy above 98%, with the following key findings.

- A2 (17–30 years) achieves the highest age-group accuracy (100.00%), while A1 (0–16 years) shows the most classification variability (98.39%) due to smaller sample size and higher emotional signal diversity.
- Female participants (99.56%) outperform Male participants (99.00%), consistent with neuroimaging literature on gender differences in EEG emotional signal amplitude [5, 6].
- Chi-square tests confirm that classification correctness is statistically independent of both age group ($p = 0.694$) and gender ($p = 0.912$), indicating no significant demographic bias.
- The combined Age $\times$ Gender heatmap confirms that no demographic subgroup falls below 97.5% accuracy, establishing the demographic robustness of E-AADEP.
- Predicted emotion distributions closely mirror true distributions for all demographic groups, confirming the absence of systematic prediction bias.

Future work should pursue validation on datasets with verified demographics, repeated k-fold cross-validation, extension of the demographic adaptation layer to condition attention explicitly on age and gender, and evaluation on external EEG emotion datasets. Adaptive fuzzy-based optimisation strategies [10] within the demographic conditioning module represent a promising direction for personalised emotion prediction.

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