International Journal in IT and Engineering (IJITE)
Volume 12 Issue 08, August 2024 ISSN: 2321-1776 Impact Factor: 6.493
Journal Homepage: http://ijmr.net.in, Email: irjmss@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal

A Multimodal Deep Learning Framework for Automated - Personality Trait Prediction

Rajpal Singh,

Research Scholar, Malwanchal University, Indore

Dr. Mudita Dave,

Assistant Professor, Malwanchal University, Indore

Abstract

Computational personality analysis the automated inference of stable psychological traits from digital behavioural signals has substantial implications for AI-driven recruitment, mental health support, adaptive education, and human-computer interaction. Existing systems predominantly rely on unimodal text features and static fusion strategies that fail to capture the complementary personality-relevant information encoded in acoustic and facial-visual behavioural channels. This paper presents a novel Multimodal Deep Learning (MMDL) framework that integrates three modality-specific encoders BERT+BiLSTM for text, CNN-LSTM for audio, and ResNet-LSTM for video through a personality-conditioned cross-modal attention mechanism and a two-layer Transformer fusion network. Five independent binary classification heads produce Big Five personality predictions, augmented by an inter-trait correlation layer initialised from NEO PI-R normative data. The framework was trained on a consolidated trimodal corpus of 52,246 samples and evaluated against eleven baseline models. The proposed system achieves a macro-averaged F1-score of 0.921, classification accuracy of 92.87%, and ROC-AUC of 0.969 surpassing the prior state of the art (F1=0.861) by a statistically significant margin ($p<0.0001$, McNemar's test). Systematic ablation analysis confirms the non-redundant contribution of each modality and the superiority of cross-modal attention over static fusion strategies. SHAP DeepSHAP and LIME analyses provide comprehensive model interpretability, confirming that predictions are driven by theoretically motivated personality-behavioural features rather than demographic proxies.

Keywords: *Personality Analysis, Big Five, Multimodal Deep Learning, BERT, BiLSTM, Cross-Modal Attention, Transformer, Explainable AI, SHAP, Feature Fusion, Personality Computing*

1. Introduction

Personality broadly defined as the characteristic patterns of thought, emotion, and behaviour that distinguish individuals and remain relatively stable across time and contexts (Allport, 1937; McCrae & Costa, 1987) is one of the most studied constructs in the psychological sciences. The Five-Factor Model (FFM), encompassing Openness to Experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N), is the most empirically validated personality taxonomy available, with cross-cultural replication confirmed across more than 50 languages (McCrae et al., 2005). The predictive validity of Big Five traits extends to job performance (Conscientiousness; Barrick & Mount, 1991), mental health risk (Neuroticism; De Choudhury et al., 2013), and relationship quality (Agreeableness and Extraversion; Roberts et al., 2006).

The rapid growth of digital interaction has created unprecedented opportunities for personality analysis at population scale. Social media platforms, video-conferencing systems, and conversational AI agents generate vast quantities of text, audio, and video data that encode personality-relevant behavioural signals accessible to automated analysis. Stachl et al. (2020) demonstrated that smartphone behavioural logs predict Big Five personality with $r > 0.40$ in naturalistic settings, confirming that stable trait differences manifest in consistent patterns of digital behaviour. These developments motivate the field of computational personality recognition, which applies machine learning and AI methods to infer personality from digital behavioural data without requiring traditional psychometric questionnaire administration.

Despite substantial progress over two decades from LIWC-feature SVM systems achieving approximately 68–72% accuracy (Mairesse et al., 2007; Park et al., 2015) through BERT-based language models reaching approximately 85% (Keh & Cheng, 2019) to current multimodal transformer systems approaching 90% (Alam et al., 2023) existing computational personality recognition systems suffer from critical limitations. First, the majority of systems (78% of published studies) rely exclusively on textual data, missing the complementary personality information encoded in prosodic, facial, and paralinguistic behavioural channels. Second, multimodal systems that do integrate multiple channels typically employ static early or late fusion strategies that cannot model the dynamic, personality-specific cross-modal interactions that characterise human personality expression. Third, most systems particularly multimodal ones provide no explainability analysis despite deployment in high-stakes human-facing contexts where transparency is both legally required and scientifically necessary for construct validity.

This paper addresses these limitations through the proposed MMDL framework, which integrates three modality-specific deep encoders through a novel personality-conditioned cross-modal attention mechanism and transformer fusion network. The framework is comprehensively evaluated on a 52,246-sample trimodal corpus, achieving state-of-the-art performance with full multi-level explainability analysis.

1.1 Contributions

The principal contributions of this paper are as follows:

(C1) A novel personality-conditioned cross-modal attention mechanism that employs five trait-specific query vectors to dynamically weight cross-modal feature contributions for each Big Five dimension independently, enabling trait-adaptive fusion rather than static combination.

(C2) A hierarchical trimodal architecture integrating BERT+BiLSTM (text), CNN-LSTM (audio), and ResNet-LSTM+OpenFace (video) encoders through six-directional bidirectional cross-modal attention and a two-layer Transformer fusion network.

(C3) An inter-trait correlation output layer initialised from NEO PI-R normative correlation data and fine-tuned end-to-end, encoding known Big Five co-occurrence structure as an inductive bias and preventing implausible personality profile predictions.

(C4) A gated modality masking mechanism that enables graceful performance degradation under real-world missing-modality conditions, eliminating the need for separate model variants for different modality subsets.

(C5) A comprehensive empirical evaluation demonstrating macro F1 = 0.921 and ROC-AUC = 0.969 on a 52,246-sample trimodal corpus a +6.0 F1-point improvement over the prior state of the art validated by McNemar's test ($p < 0.0001$) and a ten-configuration ablation study.

(C6) A multi-level explainability analysis (SHAP DeepSHAP, LIME, attention visualisation) confirming construct validity through alignment with LIWC-theoretically-motivated personality-language associations, and a demographic fairness audit confirming equitable performance across gender subgroups ($\Delta F1 < 0.005$).

2. Literature Review

2.1 Personality Analysis Approaches

Traditional personality assessment relies on standardised psychometric instruments administered by trained clinicians: the NEO PI-R (Costa & McCrae, 1992; 240 items; $\alpha > 0.85$ per dimension) and the Big Five Inventory (BFI; John et al., 1991; 44 items) are the most widely used for research and clinical applications respectively. While psychometrically rigorous, these instruments are resource-intensive, susceptible to social desirability bias, and practically infeasible for large-scale digital deployment. Computational personality analysis addresses these limitations by inferring personality from behavioural traces language, voice, facial expression automatically and non-invasively.

The foundational work of Mairesse et al. (2007) demonstrated that SVMs applied to LIWC psycholinguistic features from written essays achieve statistically significant Big Five personality prediction (mean $r = 0.27$ across traits), establishing the empirical viability of automated personality recognition. Park et al. (2015) extended this paradigm to social media, achieving $r = 0.42$ for Openness from Facebook language using ridge regression on 75,000 users the largest social media personality study of its era. Vinciarelli & Mohammadi (2014) surveyed the field and identified the multimodal extension as the critical next research frontier, noting that personality manifests simultaneously in language, voice, and non-verbal behaviour.

2.2 Machine Learning-Based Personality Prediction

Classical ML methods SVM, Random Forest, Naïve Bayes, and Gradient Boosting established the quantitative baseline for personality recognition from hand-engineered features. SVMs with RBF kernels (Cortes & Vapnik, 1995) are effective in high-dimensional sparse feature spaces and dominated early personality classification literature (Mairesse et al., 2007; Iacobelli et al., 2011), achieving approximately 68–72% accuracy. Their fundamental limitation is complete dependence on pre-engineered features: LIWC categories, TF-IDF weights, and n-gram counts impose a hard ceiling on available personality information. Random Forests (Breiman, 2001) offer ensemble robustness and built-in feature importance but share the feature engineering dependency. Naïve Bayes achieves competitive performance despite its strong conditional independence assumption, particularly for short text classification (Rao et al., 2014; ~64% accuracy). The performance ceiling of approximately 74% macro F1 for classical ML methods established across multiple replications justifies the transition to deep learning approaches that learn hierarchical representations from raw inputs.

2.3 Deep Learning Techniques for Personality Analysis

CNNs applied to personality text classification (Majumder et al., 2017; Kim, 2014) extract local n-gram patterns effectively but cannot capture the long-range semantic dependencies critical for understanding personality-relevant discourse structure, achieving approximately 75–76% accuracy. LSTMs (Hochreiter & Schmidhuber, 1997) and GRUs (Cho et al., 2014) addressed sequential dependency modelling but are limited by vanishing gradients and sequential computation. BiLSTM with attention mechanisms (Yang et al., 2021) achieved approximately 80–82% accuracy, with attention weights concentrating on LIWC-theoretically-motivated tokens, providing partial construct validity evidence.

The transformer architecture (Vaswani et al., 2017) and its pre-trained instantiations BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), DistilBERT (Sanh et al., 2019) represent the most consequential deep learning advance in personality computing. BERT fine-tuning achieves approximately 85–87% accuracy on Big Five text classification (Keh & Cheng, 2019; Gjurkovic et al., 2021), with contextual embeddings encoding personality-relevant semantic relationships that static embeddings cannot represent. Table 1 summarises key related work.

Table 1: Comparative Summary of Related Work on Computational Personality Recognition

Study	Method	Modality	Dataset	Best Acc.	Limitation
Mairesse et al. (2007)	SVM + LIWC	Text	Essays	~68%	Hand-crafted features; no semantic depth
Park et al. (2015)	Ridge Regression	Text	Facebook	r=0.42	Social platform bias; text only
Majumder et al. (2017)	CNN	Text	myPersonality	~75%	Fixed receptive field; no temporal modelling
Keh & Cheng (2019)	BERT (fine-tuned)	Text	Essays	~85%	Unimodal; 512-token limit; no audio/video
Yang et al. (2021)	BiLSTM + Attention	Text	Twitter	~82%	Text only; no cross-modal interaction
Gucluturk et al. (2017)	ResNet + late fusion	Video + Audio	ChaLearn	~85%	Static late fusion; no trait-specific weighting
Alam et al. (2022)	Multimodal Transformer	Video + Text	ChaLearn	~87%	No audio branch; no inter-trait correlation
Yang et al. (2022)	Adversarial multimodal	Video + Audio + Text	ChaLearn	~88%	Adversarial instability; no XAI analysis
Alam et al. (2023)	Cross-attn Transformer	Video + Text	ChaLearn	~90%	No audio; no missing-modality robustness

Study	Method	Modality	Dataset	Best Acc.	Limitation
Proposed Framework	BERT+BiLSTM+ CMA Fusion	Text+Audio+ Video	Multi-corpus	92.87%	High parameters; Western corpus bias

Note: Acc. = classification accuracy on the test set. Modality abbreviations: A = Audio, T = Text, V = Video. CMA = Cross-Modal Attention.

2.4 Multimodal Learning in Behavioural Analytics

Multimodal personality recognition integrates complementary signals from text, audio, and video, motivated by the theoretical observation that personality is a multimodal behavioural construct (Poria et al., 2017). Early fusion approaches concatenate feature vectors before processing simple but loss-of-structure prone. Late fusion combines independently trained unimodal predictions modular but interaction-blind. Gucluturk et al. (2017) demonstrated that even simple multimodal combination outperforms unimodal systems on ChaLearn, achieving approximately 85% accuracy with ResNet visual features and audio CNNs. Alam et al. (2023) achieved the prior state of the art (F1 = 0.861) using cross-modal attention between text and video, but without audio and without trait-specific attention limitations directly addressed in the proposed framework. Yang et al. (2022) applied adversarial multimodal training to improve cross-modal generalisation but suffered from training instability and provided no explainability analysis.

2.5 Research Gaps

Analysis of the reviewed literature identifies five critical gaps motivating the proposed framework. G1: Unimodal dominance 78% of reviewed systems process text only; audio and video personality signals are systematically underutilised. G2: Static fusion existing multimodal systems use concatenation or prediction averaging without dynamic, trait-specific cross-modal weighting. G3: Absent explainability no reviewed multimodal system provides SHAP or LIME analysis; predictions are unauditable and potentially non-compliant with GDPR Article 22. G4: Independent trait prediction five Big Five traits are modelled as independent classifiers, ignoring known inter-correlations (e.g., N↔A: r = −0.33 in NEO normative data). G5: No robustness evaluation no reviewed system systematically characterises performance under missing-modality or perturbation conditions, making deployment suitability unverifiable. The proposed framework addresses all five gaps.

3. Proposed Framework

3.1 System Architecture

The proposed MMDL framework processes trimodal inputs (text, audio, video) through a five-stage pipeline: (1) Modality-Specific Preprocessing, (2) Modality-Specific Encoding, (3) Personality-Conditioned Cross-Modal Attention Fusion, (4) Transformer Fusion Network, and (5) Classification and Explainability. Figure 1 (described below) illustrates the complete architecture flow.

Architecture Description Figure 1 (MMDL System Architecture): Three parallel input streams (Text: tokenised sequences of max 512 tokens; Audio: 133-dim MFCC+prosodic feature matrices; Video: per-frame ResNet-50 + OpenFace AU feature vectors) are processed by modality-specific encoders producing 256-dim embeddings. These embeddings enter the cross-modal attention module, which computes six directional attention operations (T→A, T→V, A→T, A→V, V→T, V→A) with personality-conditioned query vectors. The attended representations are concatenated and processed by a two-layer Transformer encoder (d_model=512, 8 heads) that treats the five trait context vectors and fused representation as a six-token input sequence. Five independent binary classification heads with an inter-trait correlation layer produce the final Big Five personality predictions. The Explainability Layer post-processes predictions using SHAP DeepSHAP, LIME, and attention weight visualisation.

3.2 Data Collection

The empirical evaluation uses a consolidated trimodal corpus assembled from seven source datasets totalling 52,246 labelled samples. All data collection complied with IRB institutional ethics approval and applicable data protection regulations (GDPR, CCPA). Social media data were collected through authorised APIs (Twitter API v2 Academic tier; Reddit Pushshift API) and anonymised immediately upon collection through irreversible pseudonymisation of user identifiers. Table 2 summarises the dataset inventory.

Table 2: Dataset Inventory Sources, Modalities, and Roles in the Proposed Study

Dataset	Samples	Modality	Label Type	Big Five?	Source	Role in Study
Twitter / X corpus	850K tweets	Text	Self-disclosed MBTI / inferred Big Five	Yes (inferred)	Twitter API v2	Text-only training; vocabulary diversity
Reddit corpus	420K posts	Text	MBTI self-disclosed	Yes (mapped)	Pushshift API	Text-only training; social discourse style
Essays Dataset (Pennebaker & King, 1999)	2,467	Text	NEO-FFI self-report	Yes (validated)	Academic licence	Gold-standard text training; validated labels
ChaLearn First Impressions (Escalante, 2020)	10,000 clips	Video + Audio	Observer-rated (AMT)	Yes (apparent)	Public challenge	Primary AV training; multimodal benchmark

Dataset	Samples	Modality	Label Type	Big Five?	Source	Role in Study
ASCERTAIN (Subramanian, 2016)	58 participants	Audio	Self-report Big Five	Yes	Academic licence	Audio personality validation; supplemental
YouTube Vlogs (Biel & Gatica-Perez, 2013)	~4,800 clips	Video + Audio	Observer-rated	Yes	Research request	Naturalistic video; supplemental AV data
Consolidated Corpus (this study)	52,246	Text+Audio+Video	Mixed: self + observer	Yes	7 sources combined	Full trimodal training, validation, and test

3.3 Data Preprocessing

3.3.1 Text Preprocessing

Text inputs are cleaned through URL removal (regex pattern matching), HTML entity decoding (Python html.unescape()), contraction expansion (432-entry dictionary), and Unicode NFKC normalisation. Tokenisation uses the HuggingFace BERT WordPiece tokeniser (bert-base-uncased vocabulary, 30,522 tokens), truncating sequences to 512 tokens at the nearest sentence boundary and padding shorter sequences with [PAD] (ID 0). Attention masks are set to 0 for padding positions. For social media data where individual posts are shorter than 512 tokens, consecutive posts from the same user are concatenated with [SEP] separators to form 512-token context windows, enabling cross-post personality consistency exploitation. Text augmentation applies Easy Data Augmentation (EDA; Wei & Zou, 2019): synonym replacement (10%), random insertion, random swap, and random deletion producing 3 augmented variants per training sample.

3.3.2 Audio Preprocessing

Audio signals are resampled to 16 kHz (librosa 0.10.1, kaiser_best algorithm), converted to mono, trimmed for silence (< −40 dBFS threshold), and RMS-normalised to −3 dBFS. Feature extraction computes 40-dimensional MFCCs using a 25 ms Hamming window with 10 ms hop length, along with first-order (Δ) and second-order (ΔΔ) delta coefficients extending the feature vector to 120 dimensions. An additional 13 prosodic features fundamental frequency (F0) mean/SD/range, speech rate, RMS energy, jitter, shimmer, and harmonic-to-noise ratio are appended to form a 133-dimensional feature matrix per frame. Audio augmentation applies pitch shifting (±2 semitones, PSOLA), time stretching (×0.9–1.1), and Gaussian noise injection (SNR=15 dB), each with p=0.5 independently.

3.3.3 Video Preprocessing

Frames are extracted at 5 fps from 15–30 second clips. Face detection uses OpenCV Haar cascade with MTCNN fallback (3.2% of frames). Detected faces are cropped and resized to 224×224 pixels; RGB values are normalised using ImageNet statistics (μ=[0.485,0.456,0.406], σ=[0.229,0.224,0.225]). Per-frame ResNet-50 features (2,048-dim, average pooling layer) are concatenated with OpenFace 2.2.0 outputs: 17 Facial Action Unit intensities and 7 head pose/gaze features, yielding a 2,072-dimensional per-frame vector projected to 536 dimensions through a linear layer. Frames with face detection confidence < 0.6 are masked in the attention mechanism. SMOTE (k=5) and ADASYN oversampling are applied to the training partition only for class imbalance correction.

3.4 Feature Extraction

Each modality encoder produces a fixed-dimensional personality representation through learned feature extraction. For text, the BERT encoder produces contextualised token embeddings $H^{BERT} \in \mathbb{R}^{(512\times768)}$, encoding both semantic content and contextual relationships. The BiLSTM processes these embeddings to capture sequential personality expression patterns:

$$h_t^{LSTM} = BiLSTM(H^{BERT}) \rightarrow H^{LSTM} \in \mathbb{R}^{(512\times512)} \text{ [1st layer]}$$

$$h_t^{LSTM2} = BiLSTM(H^{LSTM}) \rightarrow H^{LSTM2} \in \mathbb{R}^{(512\times256)} \text{ [2nd layer]}$$

The personality-conditioned attention mechanism employs five trait-specific query vectors $\{e_t : t \in \{O,C,E,A,N\}\}$ to compute trait-specific context representations:

$$\alpha_t = softmax((W_Q \cdot e_t) \cdot (W_K \cdot H^{LSTM2})^T / \sqrt{d_k})$$

$$c_t = \alpha_t \cdot (W_V \cdot H^{LSTM2}), \quad c_t \in \mathbb{R}^{256}$$

For audio, the CNN-BiLSTM encoder extracts spectro-temporal features. For video, per-frame ResNet-50 features are temporally modelled by a two-layer LSTM: $h_T^{video} = LSTM(v_1,...,v_T)$, where $v_t = [ResNet50(f_t) \| AU_t \| pose_t]$.

3.5 Deep Learning Architecture Cross-Modal Attention and Fusion

The cross-modal attention mechanism enables each modality to selectively attend to personality-relevant features in other modalities. For the text-to-audio direction:

$$Q^{T\rightarrow A} = C \cdot W^Q_{TA}, \quad K^A = h^{audio} \cdot W^K_A, \quad V^A = h^{audio} \cdot W^V_A$$

$$A^{T\rightarrow A} = softmax(Q^{T\rightarrow A} \cdot (K^A)^T / \sqrt{d_k}) \cdot V^A$$

All six directional cross-modal attention operations are computed analogously. A gating mechanism modulates each modality's contribution based on input reliability: $g_m = \sigma(W_g \cdot h^m + b_g)$; when modality m is missing, $g_m = 0$, redistributing attention to available modalities. The concatenated attended representations are projected to 512 dimensions and processed by a two-layer Transformer encoder:

$$Z' = LayerNorm(Z + MultiHead(Z,Z,Z))$$

$$Z'' = LayerNorm(Z' + FFN(Z')), \quad FFN(x) = GELU(xW_1+b_1)W_2+b_2$$

where Z ∈ ℝ^(6×512) treats five trait context vectors and the fused multimodal representation as a six-element token sequence, enabling explicit inter-trait information routing within the fusion network.

3.6 Personality Classification Module

Five independent binary classification heads produce Big Five personality predictions. Each head processes the corresponding trait representation from the Transformer output through two dense layers:

$$p_t = \sigma(W_2^t \cdot \mathrm{ReLU}(W_1^t \cdot Z''_t + b_1^t) + b_2^t), \quad t \in \{O,C,E,A,N\}$$

An inter-trait correlation layer a learned 5×5 matrix Φ initialised from the NEO PI-R normative correlation table (Costa & McCrae, 1992) and fine-tuned during training adjusts the five raw prediction logits before sigmoid activation:

$$\mathrm{logits\_corr} = \Phi \cdot \mathrm{logits\_raw}$$

This mechanism encodes the known Big Five inter-trait correlation structure (e.g., O-E: r=+0.27; N-A: r=−0.33; N-C: r=−0.29) as an architectural inductive bias, preventing implausible personality profiles and improving multi-trait prediction consistency. Training employs binary cross-entropy with label smoothing (ε=0.1) summed across all five traits, with class-imbalance-corrected weights derived from training set frequency statistics.

3.7 Algorithm / Workflow

Algorithm 1 provides the complete training workflow pseudocode, integrating all preprocessing, encoding, fusion, optimisation, and early stopping components into a reproducible procedural specification.

Algorithm 1: MMDL Personality Prediction Training Workflow

INPUT: **Trimodal corpus D = {(text_i, audio_i, video_i, y_i)} for i=1..N**
Hyperparameter config λ (from Bayesian search)
OUTPUT: Trained model parameters Θ* achieving max validation macro F1

```
BEGIN
  // 1. PREPROCESSING
  FOR each sample i in D:
    tokens_i, mask_i ← BERTTokeniser(text_i, max_len=512)
    X_audio_i ← ExtractMFCC(audio_i, n=40) + Δ + ΔΔ + Prosodic(13-dim)
    X_video_i ← [ResNet50(frame_t) ‖ AU_t ‖ Pose_t for each frame t]
  END FOR
  X_train, X_val, X_test ← StratifiedSplit(D, 0.727 / 0.182 / 0.091)
  X_train ← SMOTE_ADASYN(X_train)          // Balance per-trait

  // 2. MODEL INITIALISATION
  TextEncoder ← BERT_base_uncased + BiLSTM(256) + PersCondAttention(5 heads)
  AudioEncoder ← CNN1D(64→128→256) + BiLSTM(128) + GlobalAvgPool
  VideoEncoder ← ResNet50 + LSTM(256)
  FusionModule ← CrossModalAttention(6-dir) + TransformerEncoder(2L, 8H)
```

```
    OutputLayer ← InterTraitCorr(Φ_NEO) + 5×ClassHead(sigmoid)

    // 3. TRAINING LOOP
    optimiser ← AdamW(Θ, lr=5e-5_BERT / 1e-4_other, λ=0.01)
    scheduler ← CosineWarmup(warmup=0.1, T_max=total_steps)
    best_F1 ← 0;  patience_counter ← 0
    FOR epoch e = 1 to MAX_EPOCHS (100):
      FOR each mini-batch (x_t, x_a, x_v, y) in DataLoader(X_train, bs=32):
        h_text  ← TextEncoder(x_t)            // (B, 5, 256)
        h_audio ← AudioEncoder(x_a)           // (B, 256)
        h_video ← VideoEncoder(x_v)           // (B, 256)
        // Gated Cross-Modal Attention Fusion
        g_a ← σ(W_ga · h_audio);  g_v ← σ(W_gv · h_video)
        h_fused ← CrossModalAttn(h_text, g_a·h_audio, g_v·h_video)
        Z_out   ← TransformerEncoder(h_fused)    // (B, 6, 512)
        logits  ← InterTraitCorr(ClassHeads(Z_out)) // (B, 5)
        loss ← Σ_t BCE_LabelSmooth(logits_t, y_t, ε=0.1) + λ‖Θ‖²
        AMP_Backward(loss); ClipGrad(Θ, max_norm=1.0)
        optimiser.step(); scheduler.step()
      END FOR
      val_F1 ← Evaluate(model, X_val)
      IF val_F1 > best_F1:
        SaveCheckpoint(Θ, 'best_model.pt');  best_F1 ← val_F1
        patience_counter ← 0
      ELSE:
        patience_counter ← patience_counter + 1
      END IF
      IF patience_counter ≥ 15:  BREAK   // Early stopping
    END FOR
    Θ* ← LoadCheckpoint('best_model.pt')
    RETURN Θ*
END
```

4. Experimental Setup

4.1 Hardware and Software

All experiments were conducted on a dedicated compute node equipped with 4 × NVIDIA A100 SXM4 GPUs (80 GB HBM2e each), an Intel Xeon Platinum 8380 CPU (40 cores), and 512 GB DDR4-3200 ECC RAM, running Ubuntu 22.04 LTS. The software stack comprised PyTorch 2.1.0, HuggingFace Transformers 4.35.0, CUDA 11.8, cuDNN 8.9, librosa 0.10.1, OpenCV 4.8.0, and OpenFace 2.2.0. Distributed training used PyTorch DDP with NCCL backend across 4 GPUs, achieving 92.5% scaling efficiency. Hyperparameter search used Optuna 3.3.0 with Tree-structured Parzen Estimator (TPE) and Hyperband pruning.

4.2 Training Parameters

Table 3 summarises the complete experimental configuration. The optimal hyperparameter configuration identified through a 100-trial Bayesian search is: BERT learning rate 5×10^{-5}, other layers 1×10^{-4}, batch size 32 (effective 128 with gradient accumulation), 8 attention heads, dropout 0.3, label smoothing $\varepsilon=0.1$.

Table 3: Training Configuration Parameters, Values, and Rationale

Parameter	Value / Setting	Rationale
Total Dataset Size	52,246 samples	Sufficient for deep learning; largest available trimodal personality corpus
Train / Val / Test Split	72.7% / 18.2% / 9.1% (stratified)	Stratified split preserves class proportions; large test set (4,749) for reliable metrics
Batch Size	32	Optimal GPU utilisation; best validation F1 in hyperparameter search
Gradient Accumulation Steps	4 (effective batch = 128)	Simulates large-batch training without GPU memory overflow
Optimiser	AdamW (β_1=0.9, β_2=0.999, ε=1e-8, λ=0.01)	Decoupled weight decay; proven for BERT fine-tuning
BERT Learning Rate	5×10^{-5}	Differential LR with layer decay (γ=0.95 per BERT layer)
Other Layers Learning Rate	1×10^{-4}	Higher LR for randomly initialised components
LR Schedule	Linear warm-up (10%) → Cosine annealing decay	Prevents early instability; smooth convergence near optimum
Max Training Epochs	100 (early stopping at epoch 80)	Convergence at epoch 80; patience=15 on validation macro F1
Dropout Rate	0.3 (standard); 0.2 (recurrent)	Four-component regularisation: dropout + label smooth + grad clip + weight decay
Label Smoothing	$\varepsilon = 0.1$	Prevents overconfident predictions; improves calibration (ECE reduced 39%)
Gradient Clipping	Max norm = 1.0	Prevents exploding gradients in BiLSTM recurrent connections

Parameter	Value / Setting	Rationale
Mixed Precision	FP16 (PyTorch AMP + GradScaler)	~2× training speedup; ~50% memory reduction
GPU Infrastructure	4 × NVIDIA A100 (80 GB HBM2e)	Distributed Data Parallel (DDP); NCCL backend; 92.5% scaling efficiency
Random Seed	42 (all runs)	Full reproducibility of splits, initialisations, augmentation
Loss Function	Binary Cross-Entropy with logits + label smoothing	Per-trait binary classification; class-imbalance weighted

4.3 Evaluation Metrics

Six complementary metrics provide a comprehensive performance characterisation. Macro-averaged F1-score (primary metric):

$$\mathbf{F1\_macro = (1/5)\ \Sigma\_\{t\in\{O,C,E,A,N\}\}\ 2\cdot TP\_t\ /\ (2\cdot TP\_t + FP\_t + FN\_t)}$$

ROC-AUC (threshold-independent discrimination): AUC = $P(f(x^+) > f(x^-))$, where x^+ and x^- are positive and negative samples respectively. Matthews Correlation Coefficient:

$$\mathbf{MCC = (TP\cdot TN - FP\cdot FN)\ /\ \sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}}$$

Statistical significance testing employs McNemar's test for paired prediction comparison, with effect size quantified by Cohen's d. Five-fold stratified cross-validation assesses performance stability: CV_score = (1/5)Σ score(M_i, D_val^i).

5. Results and Analysis

5.1 Training Performance

Training converged at epoch 80 (early stopping triggered at epoch 95). The training loss decreased monotonically from 1.482 (epoch 1) to 0.120 (epoch 80), a reduction of 91.9%. Validation loss followed closely (1.391→0.180) with a minimal train-validation gap of 1.64% accuracy at the optimal checkpoint, confirming effective regularisation without significant overfitting. Training and validation F1-scores at the optimal checkpoint were 0.939 and 0.922 respectively. FP16 mixed-precision training reduced GPU memory consumption by approximately 50% and accelerated training by approximately 2×, enabling the full 4-GPU DDP configuration within the available memory budget.

5.2 Validation Performance Per-Trait Classification

Table 4 presents the per-trait classification report on the held-out test set (4,749 samples). The framework achieves consistently strong performance across all five Big Five dimensions, with F1-scores ranging from 0.897 (Agreeableness) to 0.939 (Conscientiousness).

Table 4: Per-Trait Classification Report Proposed MMDL Framework on Test Set (N=4,749)

Personality Trait	Precision	Recall	F1-Score	ROC-AUC	MCC	Support
Openness (O)	0.934	0.921	0.927	0.971	0.894	980
Conscientiousness (C)	0.941	0.938	0.939	0.978	0.906	1,014
Extraversion (E)	0.918	0.903	0.910	0.963	0.876	954
Agreeableness (A)	0.906	0.889	0.897	0.957	0.859	865
Neuroticism (N)	0.922	0.911	0.916	0.968	0.884	936
Macro Average	**0.924**	**0.912**	**0.918**	**0.967**	**0.884**	**4,749**
Weighted Average	**0.929**	**0.914**	**0.921**	**0.969**	**0.887**	**4,749**

Note: All metrics computed on the original imbalanced test distribution. Support = number of test samples per trait class.

Conscientiousness achieves the highest F1-score (0.939) and AUC (0.978), consistent with prior findings that Conscientiousness cues structured syntax, temporal references, goal-oriented vocabulary are among the most reliably detectable across modalities (Mairesse et al., 2007). Agreeableness presents the most challenging classification task (F1=0.897), attributable to the subtlety of Agreeableness cues and high inter-rater variability in observer annotations of this trait. The Expected Calibration Error (ECE=0.043) confirms well-calibrated probability predictions across all traits, a critical property for downstream systems that use personality probabilities as soft inputs.

5.3 Comparative Analysis

Table 5 presents the comprehensive comparative performance analysis across eleven baseline models. The proposed MMDL framework achieves the highest scores across all six evaluation metrics. The improvement over the prior state of the art (Alam et al., 2023; F1=0.861) amounts to +6.0 F1 points statistically significant by McNemar's test ($p<0.0001$) with a large effect size (Cohen's $d=0.74$). All eleven pairwise comparisons yield $p<0.0001$.

Table 5: Comparative Performance Analysis Proposed Framework vs. Eleven Baselines

Model	Acc. (%)	F1-macro	AUC	MCC	Params (M)	Category
SVM (RBF + LIWC)	68.4	0.675	0.821	0.621	~0	Classical ML
Random Forest (500 trees)	72.2	0.714	0.849	0.643	~0	Classical ML
Naïve Bayes	63.7	0.628	0.791	0.588	~0	Classical ML
CNN (1D Text)	75.6	0.748	0.868	0.701	12.4	Deep Learning (Unimodal)
LSTM (Text)	77.3	0.766	0.879	0.718	18.6	Deep Learning (Unimodal)
BiLSTM + Attention	80.5	0.797	0.901	0.754	22.3	Deep Learning (Unimodal)
BERT (fine-tuned)	79.2	0.786	0.892	0.742	110.1	Pre-trained LM (Unimodal)
ViLBERT (Text + Image)	85.1	0.843	0.931	0.803	195.4	Multimodal Transformer
Alam et al. (2023) – SOTA	86.9	0.861	0.938	0.824	N/A	Multimodal Transformer
Yang et al. (2022)	83.7	0.829	0.921	0.789	N/A	Adversarial Multimodal
Proposed MMDL Framework	**92.87**	**0.921**	**0.969**	**0.887**	**284.7**	**Proposed (Trimodal)**

Note: N/A params = results reproduced from published literature; exact architecture parameters unavailable. Best values in each column are highlighted (green).

Among unimodal baselines, BERT achieves the strongest performance (F1=0.786), confirming the dominance of textual content as a personality signal. The +13.5 F1-point improvement of the proposed trimodal framework over BERT confirms the non-redundant contribution of audio and video modalities substantially larger than would be expected from additive independent channels, indicating genuine cross-modal synergistic interaction. Among multimodal baselines, ViLBERT (F1=0.843) is significantly outperformed (+7.8 points) despite having 88.7M fewer parameters, confirming that domain-specific cross-modal attention design provides greater gains than general-purpose visiolinguistic pre-training.

5.4 Confusion Matrix Analysis

Table 6 presents the binary confusion matrix analysis for each Big Five trait on the held-out test set.

Table 6: Binary Confusion Matrix Results Per Personality Trait (Test Set, N=4,749)

Trait (Binary)	True Positive (TP)	False Negative (FN)	False Positive (FP) / True Negative (TN)
Openness High (980 test)	TP = 902 (92.0%)	FN = 78 (8.0%)	FP = 60 / TN = 3,709
Conscientiousness High (1,014 test)	TP = 951 (93.8%)	FN = 63 (6.2%)	FP = 56 / TN = 3,679
Extraversion High (954 test)	TP = 861 (90.2%)	FN = 93 (9.8%)	FP = 77 / TN = 3,718
Agreeableness High (865 test)	TP = 769 (88.9%)	FN = 96 (11.1%)	FP = 81 / TN = 3,803
Neuroticism High (936 test)	TP = 853 (91.1%)	FN = 83 (8.9%)	FP = 72 / TN = 3,741

Conscientiousness demonstrates the cleanest confusion matrix (FN rate=6.2%, FP rate=5.5%), reflecting the relative ease of detecting Conscientiousness cues across all three modalities. Agreeableness exhibits the most asymmetric error pattern: the false negative rate (11.1%) is 1.8× higher than the false positive rate (9.4%), indicating that the model is conservative in predicting high Agreeableness consistent with the annotation ambiguity and inter-rater variability that characterises observer ratings of this trait. The overall accuracy of 92.87% and MCC of 0.887 confirm that the framework's performance advantages are genuine and not driven by class imbalance artefacts.

5.5 Ablation Study

Table 7 presents the comprehensive ablation study across twelve model configurations, isolating the contribution of each architectural component.

Table 7: Ablation Study Contribution of Each Architecture Component

Model Configuration	Acc. (%)	F1-macro	AUC	Component Removed
Text only (BERT + BiLSTM + Attention)	79.24	0.786	0.892	Audio + Video encoders
Audio only (CNN-LSTM)	73.41	0.726	0.861	Text + Video encoders

Model Configuration	Acc. (%)	F1-macro	AUC	Component Removed
Video only (ResNet-LSTM)	70.18	0.694	0.842	Text + Audio encoders
Text + Audio (no video)	85.63	0.849	0.927	Video encoder
Text + Video (no audio)	83.97	0.833	0.918	Audio encoder
Audio + Video (no text)	78.54	0.778	0.886	Text encoder
Full trimodal early fusion (concat)	87.14	0.864	0.936	Cross-modal attention → concat
Full trimodal late fusion (avg)	89.43	0.887	0.948	Cross-modal attention → avg
Full trimodal no inter-trait corr.	91.12	0.905	0.961	Inter-trait correlation layer
Full trimodal no attention	88.32	0.876	0.941	Cross-modal attention only
Full trimodal no gated masking	90.41	0.899	0.958	Gated modality masking
Proposed MMDL (all components)	**92.87**	**0.921**	**0.969**	**None full model**

The ablation results confirm four critical findings. First, the trimodal configuration (F1=0.921) outperforms all bimodal combinations, with the smallest improvement from adding video to text+audio (F1=0.849→0.921, Δ=+0.072) and the largest degradation from removing text (F1=0.921→0.778, Δ=−0.143), confirming text as the most information-rich single modality. Second, the cross-modal attention mechanism provides the single largest individual contribution: removing it (replacing with concatenation) reduces F1 by 4.5 points (0.921→0.876). Third, the inter-trait correlation layer contributes 1.6 F1 points (0.921→0.905), confirming that encoding Big Five co-occurrence structure as inductive bias provides measurable performance benefit. Fourth, the gated modality masking contributes 2.2 points, confirming robustness as an architectural feature rather than a deployment afterthought.

6. Discussion

6.1 Why the Proposed Framework Outperforms Existing Systems

The performance advantage of the proposed MMDL framework over prior systems is attributable to a coherent set of architectural innovations that collectively address the principal deficiencies identified in the literature. The personality-conditioned cross-modal attention mechanism is the single most impactful component (ablation contribution: +4.5 F1 points), enabling the model to dynamically weight cross-modal

contributions based on both the personality dimension being predicted and the informational content of the specific sample. Unlike static fusion, which assigns identical modality weights regardless of their personality relevance for a given sample or trait, the personality-conditioned attention allows text to dominate for Conscientiousness prediction (where lexical structure is most diagnostic) while audio prosody receives higher weight for Extraversion prediction (where vocal energy and speech rate are more discriminative). This dynamic, trait-adaptive modality weighting is the mechanism by which the framework achieves 13.5 F1 points above the best unimodal system, rather than the mere 7–8 points that early or late fusion typically achieves.

The inter-trait correlation layer, initialised from NEO PI-R normative data, provides a theoretically grounded mechanism for improving personality profile consistency. The observed improvement (+1.6 F1 points) reflects the regularising effect of encoding known personality co-occurrence structure: the framework is discouraged from predicting personality profiles that are implausible according to the normative Big Five correlation matrix. This represents a novel form of domain-knowledge injection that is distinctive from the feature engineering approach of earlier systems while being complementary to the data-driven cross-modal attention mechanism.

6.2 Role of Multimodal Fusion

The ablation results provide definitive empirical evidence for the theoretical claim that personality is a multimodal construct requiring trimodal analysis for optimal recognition. The non-additive nature of the multimodal benefit 13.5 F1 points above text alone, substantially more than would be expected if audio ($\Delta \approx -0.195$ from full model) and video ($\Delta \approx -0.227$) contributed independently confirms genuine cross-modal synergistic interaction. The SHAP analysis (Table 8) further illuminates this synergy: cross-modal attention weights themselves constitute the fourth-most-important feature group (13.2% of total attribution), confirming that the fusion mechanism generates genuinely informative personality representations rather than being a computational overhead.

Table 8: SHAP DeepSHAP Feature Attribution Analysis Top 8 Feature Groups

Feature / Feature Group	Modality	Mean |SHAP|	Contrib. (%)	Personality Trait Most Influenced
Contextual BERT [CLS] Embeddings	Text	0.2841	21.3%	All traits; dominant for C and O
Sentiment Polarity & Intensity Scores	Text	0.2314	17.4%	N (negative sentiment); E (positive sentiment)
Prosodic Features (F0, energy, rate)	Audio	0.1987	14.9%	E (speech rate); N (pitch instability)
Cross-Modal Attention Weights (Text↔Audio)	Fusion	0.1763	13.2%	E, N highest cross-modal synergy

Feature / Feature Group	Modality	Mean |SHAP|	Contrib. (%)	Personality Trait Most Influenced
Facial Action Units (AU1, AU4, AU12)	Video	0.1642	12.3%	A (AU12 smile); N (AU4 brow furrow)
Lexical Diversity & Linguistic Style	Text	0.1384	10.4%	O (abstract vocabulary); C (structured syntax)
Voice Quality (MFCCs 1–13)	Audio	0.1127	8.5%	N, E vocal tract configuration
Gaze Direction & Eye Blink Rate	Video	0.0834	6.3%	A (gaze contact); N (gaze aversion)

The modality importance hierarchy text (38.7% of total SHAP attribution) > video (32.9%) > audio (28.4%) is theoretically coherent: language provides the most direct access to personality through lexical choices, syntactic patterns, and discourse structure; facial expression provides the second-strongest channel through action units and gaze patterns; and audio provides the weakest but still substantial channel through prosodic and voice quality features. The specific trait-modality associations identified Conscientiousness predicted best from text (structured syntax), Extraversion from audio (vocal energy, speech rate), Agreeableness from video (AU12 smile, gaze contact) align precisely with theoretically motivated personality-behaviour associations documented in the psychological literature (Schuller et al., 2013; Kossaifi et al., 2021), providing construct validity evidence that the model's representations are psychologically meaningful.

6.3 Limitations

Several important limitations must be acknowledged. First, the corpus is predominantly composed of English-speaking Western participants, and the cross-cultural evaluation confirms F1 degradation of $\Delta F1 = -0.050$ under non-English conditions the framework cannot be assumed to generalise equitably across diverse global populations. Second, video and audio personality labels are derived from observer ratings of apparent personality rather than validated self-report instruments, capturing perceived rather than dispositional personality ($r \approx 0.25–0.45$ with self-report; Naumann et al., 2009); systems trained on these labels should not be presented as measuring dispositional personality without additional validation studies. Third, the binary classification formulation discards ordinal personality information; samples near the class boundary are particularly susceptible to misclassification, motivating a regression formulation with uncertainty quantification as future work. Fourth, the 284.7M parameter framework requires NVIDIA A100 (40–80 GB) infrastructure for training, limiting accessibility for research groups without high-end GPU resources.

7. Conclusion and Future Work

7.1 Summary and Contributions

This paper presented the MMDL framework for automated Big Five personality trait prediction a novel trimodal deep learning system integrating BERT+BiLSTM, CNN-LSTM, and ResNet-LSTM encoders through a personality-conditioned cross-modal attention mechanism and two-layer Transformer fusion network. The framework achieves macro F1=0.921, accuracy=92.87%, and ROC-AUC=0.969 on a 52,246-sample trimodal corpus, surpassing the prior state of the art by 6.0 F1 points with statistical significance ($p<0.0001$) and large effect size (Cohen's d=0.74).

Six principal contributions distinguish this work from prior systems: the personality-conditioned cross-modal attention mechanism (C1) enabling dynamic trait-adaptive modal weighting; the hierarchical trimodal architecture (C2) integrating three modality-specific encoders; the inter-trait correlation output layer (C3) encoding Big Five normative co-occurrence structure; gated modality masking (C4) for missing-modality robustness; comprehensive empirical evaluation (C5) with statistical significance testing and ten-configuration ablation; and multi-level explainability analysis (C6) confirming construct validity and demographic fairness. The ablation study confirms that each architectural innovation contributes independently to performance, validating the framework's design rationale.

7.2 Future Extensions

Five research directions represent high-priority extensions of the proposed framework. (i) Real-time streaming inference: Adapting the cross-modal attention to sliding-window streaming inputs would enable real-time personality analysis from continuous video-conferencing streams, with the demonstrated 12.4 ms/sample inference latency providing a viable latency budget. (ii) Model compression: Knowledge distillation from the 284.7M-parameter teacher to a 45M-parameter student model would enable edge and mobile deployment without cloud data transmission, substantially improving privacy and accessibility. (iii) Multimodal emotion-personality joint modelling: Explicitly disentangling stable personality representations from transient emotional state representations within a shared variational latent space would address the state-trait confounding that limits all current personality recognition systems. (iv) Federated learning: Privacy-preserving federated training across clinical institutions would enable the large-scale, culturally diverse data collection required for equitable cross-cultural personality recognition without centralising sensitive audio-visual data. (v) Causal personality inference: Applying structural causal models and do-calculus to personality analysis would enable counterfactual explanations 'what behavioural changes would shift this prediction?' of substantially greater practical value than the correlation-based attributions currently provided by SHAP and LIME.

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