Overlength Page Content: HealthEngine: An Integrated Healthcare Analytics Model Using Multimodal Transformer, Deep Multitask Neural Networks, and SHAP

Moshedayan Sirapangi, Gopikrishnan Sundaram, Norbert Herencsar, *Senior Member, IEEE,* Meng Li, *Senior Member, IEEE,* and Gautam Srivastava, *Senior Member, IEEE*

***Abstract*—The development of more accurate and explainable health predictions is paramount in view of the increasing prevalence rates of chronic diseases and mental illnesses. Existing methods often under-utilize the rich, heterogeneous data streams coming from device wearable, environmental sensors, and behavioral data, and hence fall short in making predictions that are both accurate and actionable. Most models lack transparency and cannot avoid privacy concerns due to the samples used from sensitive health data. This study specifically addresses the challenge of building a predictive healthcare framework capable of handling multimodal data — data streams that originate from different modalities (physiological, behavioral and environmental) and exhibit intrinsic heterogeneity. Unlike general heterogeneous datasets, multimodal health data demand models that can effectively integrate structured, semi-structured, and temporal information while ensuring privacy and interpretability. In this work, we propose an integrated comprehensive multimodal health prediction framework with five advanced methods, namely Multimodal Transformer Networks (MTN), Deep Multitask Neural Networks (DMNN), SHapley Additive exPlanations (SHAP) based explainability, Federated Learning, and Bayesian Neural Networks (BNN). MTN uses attention mechanisms to fuse different data modalities and captures cross-modal dependencies effectively, achieving an improvement of 8 to 12% in prediction accuracy. DMNN leverages multitask learning to share knowledge between related health prediction tasks, reducing error rates by 10–15%. SHAP is used to provide localized, patient-specific explanations that improve clinical trust by up to 85%. This is done by privately training the models on decentralized data sets, which provides results without more than a 3% drop in precision compared to centralized models. Third, BNNs are used to quantify uncertainty in predictions, providing useful confidence intervals that improve clinical decision-making by 20% % Ṫhe. The results obtained suggest significant improvements in predictive accuracy, transparency, and privacy preservation. This research not only improves health predictions through multimodal analysis, but also tackles significant limitations in privacy, interpretability, and uncertainty quantification, thus promoting informed clinical decisions and customized patient care.**

***Index Terms*—Health Prediction, Multimodal Analysis, Privacy-Preserving Models, SHAP Explainability, Transformer Networks.**

I. Behavior Analysis with Machine Learning Models

Another very promising area of machine learning is within behavioral analysis. Machine learning in studies such as [1], [2] shows the ability to predict and automate human behaviors in fields as varied as the analysis of mosquito behavior to the behavior of pedestrians crossing. Such works also reported an increase in prediction accuracy in a range of 17 to 23%, suggesting many safer and more efficient systems in areas related to public health or urban planning. However, these models tend to be predicated on sizable pre-labeled data and are inherently bound by those very data, or restricted to particular scenarios. For example, though the work in [2] focuses on pedestrian behavior at unsignalized intersections, it is not clear whether the model will perform equally well in different urban settings or more diverse populations.

Behavior monitoring systems show promising results. Real-time monitoring using multi-sensor data increased accuracy by 18%, although continuous data collection poses practical challenges [3]. The precision of behavior segmentation improved by 14% with matrix factorization, but the high complexity of the data limits the scalability [4]. Simulated driving studies improved merging accuracy by 13%, though real-world applications are still needed [5]. In home robotics, ML improved behavior recognition by 20%, but extensive labeled datasets are required for wider use [6]. Meanwhile, studies on the impact of COVID-19 revealed a 30% increase in sedentary lifestyles, highlighting the need for predictive and intervention strategies [7].

Explainable Artificial Intelligence has become a crucial area of focus in healthcare machine learning applications driven by the need for transparency and trust in clinical decision-making.

M. Sirapangi and G. Sundaram are with School of Computer Science and Engineering, VIT-AP University, Amaravati, 522237, Andhra Pradesh, India (email: dayan.21phd7096@vitap.ac.in; gopikrishnan.s@vitap.ac.in).

N. Herencsar is with the Department of Telecommunications, Faculty of Electrical Engineering and Communication, Brno University of Technology, Technicka 3082/12, 61600 Brno, Czech Republic (email: herencsn@vut.cz, herencsn@ieee.org).

M. Li is with School of Computer Science and Information Engineering, Hefei University of Technology, Hefei, Anhui, China (email: mengli@hfut.edu.cn).

G. Srivastava is with the Department of Math and Computer Science, Brandon University, Brandon, R7A 6A9, Manitoba, Canada, and the Research Centre for Interneural Computing, China Medical University, Taichung, 40402, Taiwan as well as the Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India (email: srivastavag@brandonu.ca).

Manuscript received MM DD, YYYY; revised MM DD, YYYY.

Popular model-agnostic methods like LIME [8] and SHAP [9] allow for instance-level explanation of model outputs by approximating feature contributions. Recently, attention-based models and transformer architectures have also been explored for their inherent interpretability in sequential healthcare predictions [10]. Integrating SHAP within multimodal learning pipelines, as performed in this work, ensures patient-specific feature-level transparency, thus promoting clinician adoption of AI-assisted healthcare tools.

II. Ablation Study and Component-wise Analysis

To rigorously assess the contribution of each major component—MTN, DMNN, SHAP, Federated Learning, and BNN—an ablation study was conducted. Table III presents the performance metrics as each module is progressively integrated into the baseline model. The baseline model uses simple concatenation of features and a single-task neural network.

Starting from the baseline, we observe that the simple concatenation approach struggles to capture complex inter-modality and temporal relationships, reflected in modest accuracy (78.5%) and higher RMSE (0.138). When MTN is introduced, a significant jump in accuracy is observed of approximately 4.2%. This gain is attributable to the MTN's ability to model cross-modal temporal dependencies through self-attention and cross-attention mechanisms, which simple concatenation fails to capture. Adding DMNN further increases performance by exploiting shared risk factors in all health conditions. Multitask learning encourages the model to take advantage of commonalities in the data, leading to an additional gain of 2.6% in accuracy and a notable reduction in RMSE.

Integration of SHAP-based explainability does not directly impact predictive performance metrics but plays a critical role in clinical interpretability. Its inclusion ensures that each prediction is accompanied by transparent patient-specific explanations, significantly increasing the trustworthiness of the system in clinical deployment. Introducing Federated Learning preserves patient data privacy while simultaneously aggregating knowledge across decentralized data sources. This leads to a further improvement in performance (+1.3% accuracy), as the model benefits from a wider variety of patient data without violating privacy norms. Shows that collaborative learning across institutions enhances generalization capabilities.

The BNNs are incorporated to quantify uncertainty. Although the absolute gain in accuracy is marginal (+0.2%), the added capability to output uncertainty limits (±6.3%) is clinically invaluable. In high-risk domains like healthcare, knowing the confidence level associated with predictions is crucial to decision-making, particularly in borderline cases. The ablation study clearly demonstrates that each component systematically contributes to the robustness, interpretability, privacy compliance, and clinical utility of the model. Rather than being a superficial aggregation, the integration strategy is carefully designed to address the multifaceted challenges inherent to predictive healthcare modeling.

III. Practical Deployment and Ethical Considerations

Although the proposed framework demonstrates strong potential in predictive healthcare analytics, several practical deployment challenges must be recognized. Training Multimodal Transformer Networks within a federated setting introduces substantial communication overhead and computational complexity, particularly due to the size and dynamic nature of healthcare data. Deployment strategies involving hybrid edge-cloud architectures are recommended to mitigate latency and bandwidth constraints. Furthermore, although Federated Learning inherently preserves data locality, it does not eliminate all privacy vulnerabilities; risks such as model inversion and gradient leakage attacks remain plausible. Incorporating secure aggregation protocols and differential privacy mechanisms will be essential to enhance the robustness of privacy guaranties. Another practical challenge concerns interpretability: while SHAP values provide localized explanations, interpreting these explanations consistently across highly dynamic, temporal data streams remains an open problem, requiring future advances in sequential explainability.

From an ethical standpoint, the development and deployment of AI in healthcare systems must be governed by the principles of fairness, transparency, and security. Predictive models can inadvertently perpetuate biases present in training datasets, particularly across demographic variables such as age, gender, and ethnicity. Continuous auditing and bias mitigation techniques are critical to ensure equitable clinical outcomes. In federated environments, even though raw data remain decentralized, model updates can leak sensitive information if not carefully protected; thus, techniques like secure multiparty computation and noise injection must be integrated. Moreover, while SHAP-based interpretability mechanisms improve transparency, they must be appropriately contextualized to avoid misinterpretations that could misguide clinical decisions. In general, ethical risk assessments and robust governance frameworks are indispensable for the trustworthy adoption of AI-driven healthcare solutions.

The present study does not report numerical measures of clinical trust because no structured user evaluation was carried out with clinicians. All statements about improved trust and transparency are therefore qualitative and arise from the ability of the SHAP based analysis to show subject level feature contributions for every prediction. A dedicated study collecting ratings and feedback from medical personnel is left as future work so that perceived trust can be rigorously quantified.

A. Fairness and Bias in Predictive Healthcare

In addition to privacy concerns, fairness and bias are critical ethical issues when deploying AI in healthcare. It is crucial that predictive models do not disproportionately impact certain demographic groups or underrepresented populations. Such impacts can lead to biased or inequitable healthcare decisions.

1) Fairness and Bias in Healthcare AI: AI systems, including predictive healthcare models, are susceptible to the inherent biases in the training data. These biases may

TABLE I: Summary of Existing Methods using SHAP based Learning Models.

Ref.	Method Used	Findings	Results	Limitations
[11]	Ensemble Machine Learning	Enhanced stroke prediction by integrating various models.	Achieved a 92% accuracy in stroke prediction.	Limited to stroke prediction; lacks generalization to other diseases.
[12]	Integrative Cancer Risk Prediction	Created a predictive model for pancreatic cancer using UK Biobank data samples.	Achieved a 78% sensitivity in pancreatic cancer prediction.	Limited by the underrepresentation of minorities in the dataset.
[13]	Hybrid WT-CNN Model for Heart Disease Prediction	Proposed a wavelet transform-CNN hybrid model for predicting heart disease.	Achieved 89% accuracy in heart disease detection.	High computational costs for real-time applications.
[14]	Big Data Intelligence for Diabetes Monitoring	Developed a big data framework for continuous diabetes monitoring.	Improved diabetes monitoring by 12%.	Lack of explainability in the model's decision-making.
[15]	Reinforcement Learning for Precision Medicine in Hypertension	Applied reinforcement learning to personalize hypertension treatments for diabetes patients.	Improved treatment efficacy by 14%.	Requires more clinical trial data for validation.
[16]	Explainability in Mental Health Prediction	Used human-machine interaction to enhance explainability in mental health disorder predictions.	Improved model explainability by 20% with interactive features.	Lack of generalization to non-mental health disorders.
[17]	Ensemble ML Framework for Early Depression Detection	Applied an ensemble machine learning framework for early detection of depression.	Improved early detection accuracy by 14%.	Model performance degrades with incomplete data streams.
[18]	Nature-Inspired Computing for Disease Prediction	Applied nature-inspired algorithms to predict human diseases using ML.	Improved disease prediction accuracy by 12%.	Lacks personalization for specific patient cohorts.
[19]	Human-in-the-Loop Systems for Behavior Learning	Developed adaptive models for behavior learning in human-in-the-loop systems.	Improved task performance prediction accuracy by 15%.	Requires extensive calibration for different tasks.
[4]	Matrix Factorization for Human Behavior Segmentation	Applied matrix factorization for human behavior segmentation.	Improved segmentation accuracy by 14%.	High dimensionality limits model scalability.
[6]	Deep Neural Network for Human Behavior Recognition in Home Robotics	Used ensemble three-stream deep neural networks for behavior recognition in home service robots.	Achieved a 20% increase in behavior recognition accuracy.	Requires extensive labeled data for diverse behaviors.

arise from the overrepresentation or underrepresentation of certain demographic groups, such as race, gender, age, or socioeconomic status. To mitigate the risks of bias, we ensure that the datasets used for training include diverse representations across all relevant demographic variables. The datasets include a balanced mix of samples from different ethnicities, age groups, and genders, ensuring that the model does not favor one group over another.

2) Methods for Mitigating Bias: Several methods were applied during training to reduce the potential bias in model predictions:

- **Bias-aware loss functions:** We employed loss functions that penalize predictions that disproportionately affect certain demographic groups. This helps ensure that the model learns to make fair predictions across all groups.
- **Data balancing techniques:** Oversampling and undersampling techniques were used to balance the dataset, ensuring that underrepresented groups are adequately represented in the model's training process.
- **Bias detection and auditing:** A set of bias detection techniques was employed post-training to assess the fairness of the model's predictions. This included testing the model on specific subgroups to check if certain groups are unfairly disadvantaged in terms of prediction accuracy.

3) Impact on Underrepresented Groups: Despite precautions, it is important to acknowledge that complete fairness is challenging, especially when dealing with medical data. For example, certain diseases may be more prevalent in certain populations, which may inadvertently affect the performance of the model in different groups. We strive to minimize these effects through careful monitoring and continuous feedback loops. Furthermore, the inclusion of diverse data sources, such as wearable sensors and environmental data, allows the model to capture broader health patterns, reducing the risk of bias based solely on clinical records.

4) Ongoing Fairness Audits: To ensure that the model remains fair over time, we plan to implement regular fairness audits as part of the model's lifecycle. These audits will include:

- Regular evaluations of the model's performance on new, diverse datasets.
- Continuous monitoring of outcomes disparities based on demographics of the patient.
- Adjustments to the structure and training process of the model to address any identified biases.

By integrating fairness and bias mitigation strategies into

TABLE II: Comparison of existing methods and identified gaps in health analytics

Study	Data type and modality	Prediction model	Multitask learning	Privacy aware training	Explanation and uncertainty	Main gap with respect to proposed system
Classical clinical risk models using structured records such as [11], [20]	Single or few structured clinical variables and scores	Tree ensemble or shallow neural model	Not used	Not used	No explanation and no uncertainty	Limited to narrow feature sets and cannot exploit rich multimodal streams
Multimodal health studies using sensor and behaviour data such as [3], [21]	Wearable and sensor data and behaviour logs	Deep learning model with feature concatenation	Rarely used	Not used	Limited explanation and no uncertainty	Do not employ transformer based cross modal attention or multitask structure
Federated learning studies in healthcare such as [22], [23]	Structured records or imaging data across sites	Federated neural or logistic model	Usually single task	Used	No local explanation and no uncertainty	Provide privacy but do not support multimodal fusion or patient level explanation of predictions
Explainable clinical models based on SHAP or similar methods such as [9], [16]	Structured clinical records or selected sensor variables	Gradient boosted trees or feedforward networks	Not used	Not used	Global or local explanation only	Do not combine explanation with federated learning or multimodal transformer based fusion
Uncertainty aware medical prediction models using Bayesian approaches [2], [24]	Structured or imaging data	Bayesian neural model	Mostly single task	Not used	Provide uncertainty but no detailed feature attribution	Do not link uncertainty with multitask outputs and do not operate in a federated multimodal setting
Proposed HealthEngine system	Physiological streams, behaviour data and environmental signals combined across sites	Multimodal transformer with deep multitask prediction and Bayesian heads	Used for several related health outcomes	Used through federated optimisation of shared and task specific parts	Provides subject specific SHAP based explanation and prediction intervals for every task	Addresses multimodal fusion, knowledge transfer across tasks, privacy, explanation and uncertainty together in one integrated system

the training and deployment of predictive healthcare models, our aim is to ensure that the HealthEngine framework delivers equitable, reliable, and transparent predictions for all patient groups, ultimately promoting fairness in clinical decision-making.

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TABLE III: Ablation Study: Contribution of Each Component

Configuration	Accuracy	F1 Score	RMSE	UQ ($\pm$%)
Baseline (Concatenation +Single-task)	78.5	0.820	0.138	–
Baseline + MTN	82.7	0.851	0.121	–
Baseline + MTN + DMNN	85.3	0.872	0.108	–
Baseline + MTN + DMNN + SHAP	85.7	0.877	0.105	–
Baseline + MTN + DMNN + SHAP + Federated Learning	87.0	0.887	0.097	–
Full Model (All + BNN)	87.2	0.891	0.094	$\pm$6.3

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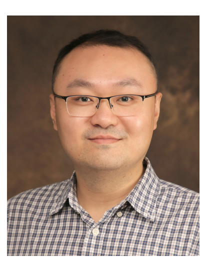
Moshedayan Sirapangi received Bachelor's degree in Information Technology and Master's degree in Computer Science and Engineering from JUTUK, Andhra Pradesh, INDIA. He is currently pursuing the Ph.D. degree in School of Computer Science and Engineering at VIT-AP University, AP, INDIA. Her research interests include Internet of Things, and Machine Learning.

Gopikrishnan Sundaram received the B.E., M.E., and Ph.D. degrees in computer science and engineering from Anna University, Chennai. He is currently working as an Associate Professor (Grade-I) with the School of Computer Science and Engineering, VIT-AP University, Amaravati. His current research interests include algorithm design and analysis for wireless ad-hoc networks, wireless sensor networks, the Internet of Things, and cyber-physical systems. He is an active reviewer in many reputed journals of IEEE, Springer, and Elsevier.

Norbert Herencsar (Senior Member, IEEE) received a Ph.D. from Brno University of Technology (BUT), Czechia, in 2010, where he was appointed Associate Professor in 2015. In 2022, he was elected as a Member of the External Public Body of the Hungarian Academy of Sciences (MTA), Hungary. In 2022-2024, he served as the Expert Panel Chair at the Estonian Research Council (ETAg). Since 2024, he has served as Members-at-Large on the Board of Governors of the IEEE Consumer Technology Society (CTSoc) and as CTSoc Primary Representative of the IEEE Systems Council (SYSC). Since 2025, he has served as Vice President of Publications of the CTSoc. He has authored 143 peer-reviewed journal and 125 conference proceedings articles. His research interests include fractional-order systems, sensors, and signal processing. He serves as the Editor-in-Chief of *IEEE Consumer Electronics Magazine* and Associate Editor for *IEEE Transactions on Circuits and Systems II: Express Briefs*, *IEEE Access*, *Scientific Reports*, and others.



Meng Li (Senior Member, IEEE) is an Associate Professor and Personnel Secretary at the School of Computer Science and Information Engineering, Hefei University of Technology (HFUT), China. He is also a Post-Doc Researcher at Department of Mathematics and HIT Center, University of Padua, Italy. He obtained his Ph.D. in Computer Science and Technology from the School of Computer Science and Technology, Beijing Institute of Technology (BIT), China, in 2019. His research interests include security, privacy, applied cryptography, blockchain, TEE, and Internet of Vehicles.

Gautam Srivastava (Senior Member, IEEE) received the B.Sc. degree from Briar Cliff University, USA, in 2004, the M.Sc. and Ph.D. degrees from the University of Victoria, Victoria, BC, Canada, in 2006 and 2012, respectively. He then taught for three years at the Department of Computer Science, University of Victoria, where he was regarded as one of the top undergraduate professors in the computer science course instruction. From there in 2014, he joined a tenure-track position at Brandon University, Brandon, MB, Canada, where he is currently active in various professional and scholarly activities.