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Original Article

Gamt-Care: A Graph Attention Multimodal Transformer Framework for Crm-Augmented Predictive Healthcare Analytics

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Abstract - *The explosion of digital healthcare services has resulted in massive amounts of patient data being collected by hospitals through their CRM systems, including appointment records, follow-ups, and communications with patients about their treatment. Unfortunately, the vast majority of predictive healthcare models today primarily utilize EHR data and largely ignore the behavioral insights that are present in CRM interaction data. To overcome this limitation, this study developed a new intelligent framework for predictive healthcare analytics and AI-enhanced clinical workflow management called GAMT-CARE (Graph Attention Multimodal Transformer for CRM-Augmented Risk Estimation). This framework introduces a new type of patient interaction graph (PIG) that models the various relationships between patients, providers, treatments, and post-treatment communications as they relate to the CRM systems used by hospitals. In order to effectively analyze the heterogeneous data associated with the healthcare ecosystem, a hybrid deep learning architecture known as the GAMTNet (Graph Attention Multimodal Transformer Network) was developed. This model utilizes medical imaging features computed using EfficientNetV2, temporal patient histories modelled using bi-directional long short term memory (Bi-LSTM), and CRM interaction patterns learned through graph neural networks (GNNs) to create a single multimodal representation of each patient's clinical, behavioral, and temporal characteristics that can be fused together using a transformer-based attention mechanism to model the complex relationships among these three different types of features. Additionally, a hybrid swarm intelligence optimization strategy based on the Adaptive Predator Swarm Optimization (APSO), a hybrid bio-inspired optimization algorithm that combines the aggressive swarm behavior of red piranhas (RPO) with the cooperative hunting strategy of grey wolves (GWO) for efficient feature selection and hyperparameter tuning, improves model performance. The suggested approach supports intelligent clinical workflow optimization and individualized healthcare intervention by enabling early prediction of patient risk levels, disease development, and hospital readmission probability.*

Keywords - *GAMT-CARE; Healthcare; CRM; GAMTNet; EfficientNetV2; APSO.*

1. Introduction

The rapidly expanding digital health care system has contributed to the exponential increase in patient-specific data related to health care through existing customer relationship management system's (CRM) usage in hospitals and other health care areas [1,2]. These systems capture all types of structured and unstructured data, which includes information at both patient demographic and appointment history level, records of follow-up and treatment communication, satisfaction surveys and engagement with the health care provider [3]. The diversity and massiveness of these data ultimately provide an unparalleled opportunity for unified predictive health care analytics by providing data from multiple sources to engage in data-driven decision-making and provide individualized patient care based on available data [4,5]. Historically, predictive health care modelling relies primarily on clinical data like laboratory results, images and electronic health records (EHR) [6]. Although these sources provide ample medical information, they have not typically included behavioral, temporal and interactional data about patient engagement that greatly impact health outcome [7]. Therefore, CRM provides a new source of longitudinal data to better understand patient adherence, response to treatment and provider communications. Thus, incorporating CRM data into traditional clinical data set can lead to more complete, accurate and comprehensive predictive models [8]. In addition to providing additional data, CRM provides predictive health care analytics through multiple disparate data sources through advanced data mining and machine learning methods.

Healthcare CRM solutions built on cloud platforms such as Salesforce Health Cloud have enhanced the ability to manage and analyze patient data over the last several years [9]. This platform is tailor-made for the health service industry; with it, healthcare providers can pull together patient information from a number of disparate sources (for example, electronic health records, wearable technologies and patient interactions) to create one complete view of every patient. Providers can access real-time patient data, coordinate patient care and engage patients on an individual basis by providing them with intelligent workflows and AI-based insight. The use of CRM technology increases the effectiveness of healthcare organizations to improve their patient relationships and care delivery processes through predictive analytics by incorporating both behavioral information and clinical data. In addition, the scalable cloud-based environment provides a foundation for interoperability and secure data sharing between systems, thereby addressing the challenges posed by data and fragmented healthcare systems. When platforms such as Salesforce Health Cloud are integrated into predictive healthcare models, the ability to provide data-driven and proactive patient-centric care is further enhanced [10]. High-risk patients can be identified, illness development can be predicted, appointment scheduling can be optimized, and medication adherence can be enhanced by using techniques including classification, clustering, and time-series analysis [11,12]. Additionally, deep learning models improve prediction accuracy and robustness by capturing intricate nonlinear interactions in multimodal data. The use of CRM-based analytics provides numerous benefits for healthcare organizations through the application of proactive healthcare approaches [13].

Through patient interaction trend and engagement metrics analysis, healthcare organizations can detect potential health declines, missed follow-ups, etc., before they happen. As a result, organizations can intervene effectively to prevent hospital readmissions and improve patient satisfaction [14]. CRM systems also allow healthcare organizations to develop more personalized communication methods with patients by providing tailored reminders and health recommendations and offering support according to individual patient needs [15]. While the use of CRM data in such predictive healthcare applications is promising, several barriers inhibit the use of this information in developing predictive healthcare systems, including the heterogeneity of data; the lack of privacy; missing data; and, in some cases, the lack of interoperability between systems. Therefore, it is critical that organizations ensure data security and compliance with healthcare regulations when dealing with sensitive patient data [16]. Furthermore, there is still a need to establish scalable and efficient models capable of processing large amounts of CRM data in real-time. The inclusion of predictive healthcare analytics with CRM data combined with clinical intelligence will create a new paradigm of next-generation healthcare systems that can provide more precise predictions and personalized care for patients while also improving overall healthcare outcomes [17]. The purpose of this study is to examine advanced methodologies for integrating CRM data into predictive models, which will thereby promote the development of patient-centered intelligent solutions to healthcare.

The following is a summary of this study's main contributions:

- This work proposed a novel intelligent healthcare framework named GAMT-CARE that integrates CRM interaction data with clinical and imaging data to enhance predictive healthcare analytics and clinical workflow management.
- This work introduced a PIG to model complex relationships among patients, clinicians, treatments, and follow-up communications, enabling effective utilization of behavioral insights derived from CRM systems.
- This work developed a hybrid deep learning architecture, GAMTNet, which combines EfficientNetV2 for medical image feature extraction, Bi-LSTM for temporal patient history modeling, and GNN for capturing CRM-based interaction patterns.
- This work implements a transformer-based multimodal fusion mechanism to integrate heterogeneous data representations and capture intricate dependencies among clinical, behavioral, and temporal features.
- This work proposes a hybrid swarm intelligence optimization strategy based on APSO, which combines GWO and RPO for effective feature selection and hyperparameter tuning.

The rest of this paper is organized as follows. The section 2 provides both related works and problem statement. The proposed methodology is explained in the section 3. The result and discussion are then presented in the section 4, followed by the conclusion in the section 5.

2. Literature Review

In 2022, Gangula [18] assessed Salesforce Health Cloud as a sophisticated patient relationship management (PRM) solution, emphasizing its functional capabilities and design. By providing uniform and real-time patient data access, the platform serves as a "system of engagement," improving traditional electronic health records. By successfully addressing major implementation issues such high deployment costs, integration complexity, and organizational adaptation, it promotes successful digital transformation and increased patient involvement.

In 2024, Topuz, et al. [19] shall propose and explainable analytic framework for primary care appointment scheduling system's no-show variation throughout multiple available day/time assigned slots. The projected no-show probabilities accomplished through a probabilistic greedy scheduling approach utilizing marginal analysis shall be used to: optimize the assignment of appointment booking to each available slot during the day increasing service quality, increasing resource utilization by determining the level of overbooking.

In 2023, Agarwal and Pal [20] developed HierChain, a blockchain based solution providing secure and efficient means of managing and sharing healthcare data. The benefit of HierChain resides in the decentralized, immutable nature of the blockchain providing a means to establish a trustless system. In addition, they formulate and solve an optimization problem to identify the best strategy for storing health care data by type/sensitivity of data and ultimately spread those datasets across multiple blockchain providers.

In 2024, Deina, et al. [21] provide a comprehensive analytical framework for addressing class imbalance in prediction accuracy. A dual application of z-fold cross validation will be applied to develop a level of robustness/generalizability to the predictive model.

Furthermore, symbolic regression will be tested as an alternate classification methodology and instance hardness threshold will be employed for resampling.

In 2022, Awotunde, et al. [22] integrated a cloud based big data analytic framework within IoT to enhance performance through increased utilization of device resources by providing an IoT/cloud system for real-time storage / advanced analysis of data generated from sensors deployed in the physical world.

In 2024, Bandi et al. [23] examined how large-scale health data and machine learning could assist in early disease detection, predict patient condition, and create optimized treatment strategies. Applications for this research include resource management and risk assessment, while also addressing data privacy and ethical concerns. This publication recommends integrating predictive models within healthcare systems to better utilize resources, decrease costs, and provide proactive personalized patient care.

Shishebori et al. [24] proposed a conceptual framework analyzing the impact of components such as customer knowledge management and technology-based CRM technologies on key organizational capabilities, including innovation, adaptability, and flexibility to enhance resilience in 2025. This research will explore mediating effects of risk and crisis management. Dastjerdi et al. [25] utilized a novel integrated framework based on Human, Technology, Organization, Environment, and Cost (HTOEC) dimensions for evaluating CRMS adoption by hospitals in 2023. Furthermore, the researchers used the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) methodology to evaluate the interrelationships and causal dependencies among identified factors affecting CRMS adoption and offer more in-depth analyses of the dynamics affecting CRMS implementation.

In 2024, Ala et al. [26] developed a novel framework that leverages AI–IoT integration to enhance the quality of patient care and optimize data processing in healthcare environments. An improved hybrid model, combining particle swarm optimization (PSO) with long short-term memory (LSTM), is introduced to boost classification performance. The PSO-LSTM approach is evaluated against traditional PSO to achieve better accuracy and efficiency.

In 2025, Wani et al. [27] proposed a framework for privacy-preserving federated learning (FED-EHR) that is specifically tailored to meet the demands of healthcare environments which utilize the Internet of Medical Things. In this environment, numerous wearable devices and smart health devices are continuously generating vast amounts of sensitive physiological data (e.g. cardiac signals, glucose levels, vital signs). Rather than using a centralized machine learning approach (which may expose patient data or break regulations such as HIPAA and GDPR) FED-EHR provides a method for training machine learning models in a decentralized manner using distributed datasets containing patient medical records stored in electronic format.

In 2026, Melhem et al. [28] developed a novel framework called C2SecFL which incorporates an adaptive, model-aware clustering method with functional encryption using inner products to secure the aggregation of federated models. This eliminates the need for a centralized key distribution center. The authors extended the concept of secure aggregation using functional encryption to be able to provide a lightweight permissioned blockchain based method for ensuring tamper proof coordination and auditability of federated learning across clusters.

2.1. Problem Statement

Existing methods used for predictive analytics in healthcare primarily employ clinical information sources (e.g. electronic health records (EHRs), laboratory results, medical imaging) to provide diagnostic information; however, they are largely unable to account for important patient behavioural, engagement, and communication factors that can significantly alter the patient's treatment outcomes. These limitations result in reduced accuracy and effectiveness of predictive models for actual healthcare applications. Patient-centric data is generated through hospital CRM systems such as tracking appointment attendance, follow-up calls, and communication logs; however, this type of data is not currently being utilized very well or included in more traditional healthcare analytics systems. The separation of clinical data and CRM data creates a disconnect that prevents the development of truly comprehensive and predictive patient-centric models. In addition, CRM data comes in many forms - it is constantly changing and is often unstructured, which introduces significant challenges when preparing, extracting and integrating data into models. The presence of missing data, noise and inconsistencies will also reduce the reliability of models built using this data. Finally, issues of privacy, security and scalability further complicate effective implementation of this type of data. As a result, there is an urgent need for an advanced, integrated healthcare analytics framework with predictive modeling capabilities that can integrate multiple sources of CRM and clinical data, handle the data complexity, and produce accurate and proactive results to support patient-centered healthcare decision making.

3. Proposed Methodology

The method of utilizing predictive analytics in healthcare through CRM-based prediction is designed to enhance the ability to make accurate predictions about patient risk by utilizing all available patient interaction data from CRM systems integrated with clinical data and imaging data. This technique captures behavioral, temporal, and relational patterns allowing for the early detection of risk and the provision of personalized care. Unfortunately, CRM-based predictive analytics systems encounter several barriers, including limited or no data capture of patient interactions, challenges in integrating multiple modalities of data, and a lack of interpretability. Solutions for addressing these barriers include the conjuncture of graph-based modelling, multimodal deep learning, and optimization techniques. This combination will not only increase prediction accuracy and increase the utility of data but also provide reliable decision-making. Figure 1 represents the GAMT-CARE framework that integrates CRM, electronic health record (EHR), and imaging data through graph-based modelling and deep learning methods that combine transformer fusion and optimization to predict patient risk levels and support clinical decision-making.

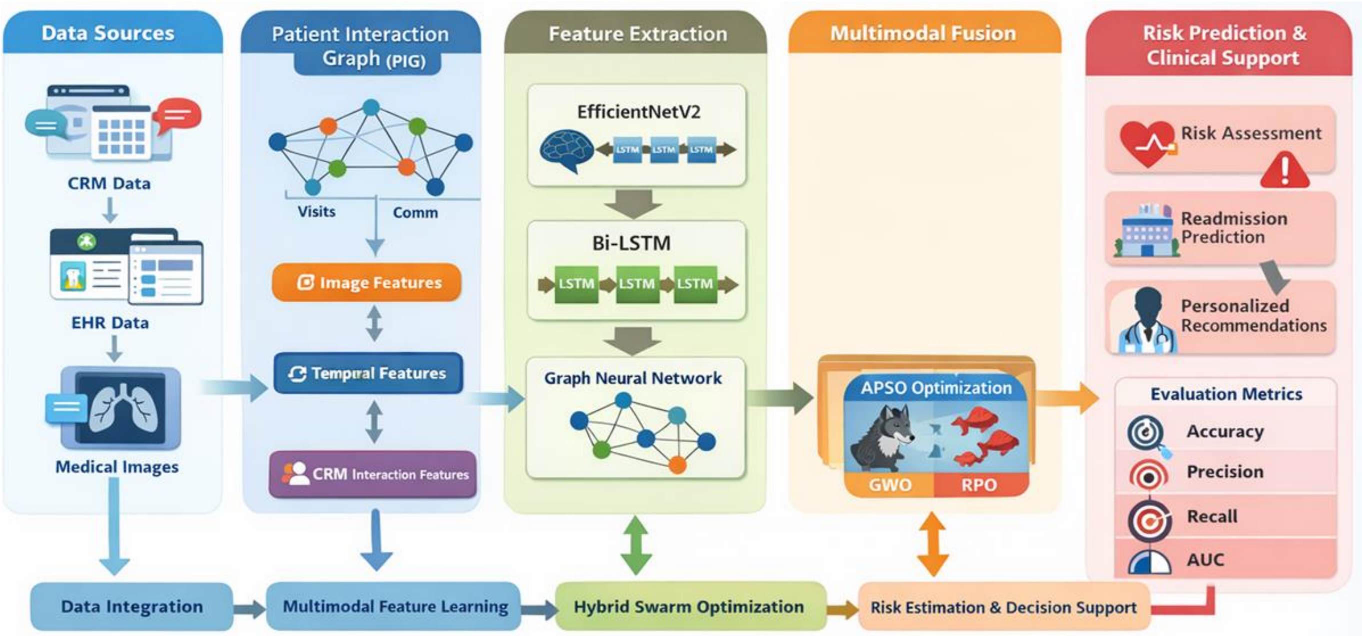

Fig 1: Architecture of the Proposed GAMT-CARE Framework for CRM-Augmented Predictive Healthcare Analytics

3.1. Data Preprocessing

A crucial step in the suggested methodology is data preparation, which guarantees the consistency, dependability, and appropriateness of diverse healthcare data for subsequent learning tasks. To improve data quality and model performance, preprocessing in this work entails comprehensive data cleaning, standardization, encoding, and temporal alignment. To address missing values and noisy records that are frequently found in healthcare datasets, data cleaning is first carried out. Statistically sound imputation methods, such as mean or median substitution for numerical attributes and mode-based imputation for categorical variables, are used to deal with missing values. In cases where too much data is missing, a careful filtering method is employed to eliminate any bias caused by this incomplete data. Statistical procedures are used to calculate and identify noisy or extreme values and then removed from the data or corrected to maintain data quality. Afterward, the continuous variables in the data are normalized (re-scaled). Normalizing features will result in them having a uniform scale and aid the convergence of learning algorithms. The various methods used to transform feature values into a consistently scaled range include: Min–Max Normalization and Z-score Standardization. These methods will also ensure that features with larger magnitudes are not dominant during model training.

To convert categorical variables to machine-readable formats, various encoding techniques are used. Label encoding is used for ordinal variables, and one-hot encoding is used for nominal variables (to preserve the independence between the categorical classes that do not introduce any unintentional ordinal relationships). Given the temporal nature of patient interactions, temporal sequence alignment is performed to format the longitudinal patient data (appointment history, follow-up visits, and treatment timelines). Time-series records are then transformed into a consistent sequential structure that allows for proper learning by temporal models (e.g., Bidirectional Long Short-Term Memory networks) in order to accurately capture the sequential dependencies and trending patterns present in patient data.

Advanced healthcare CRM solutions like Salesforce Health Cloud, which include unified patient profiles, interaction logs, and real-time engagement data, are an efficient source of the CRM interaction data used in this framework. These systems facilitate the creation of the PIG and improve the overall efficacy of predictive healthcare analytics by enabling the smooth integration of behavioral and clinical data.

3.2. PIG Construction

A PIG contains structured health data that allows us to visualize the interaction of clinical entities and patient interactions based on CRM data. The new approach includes an adaptive edge-weighting mechanism that accounts for frequency, recency, and patient engagement in order to enhance the representation of behavior-based relationships beyond what conventional health graphs can provide. Additionally, the PIG is defined using heterogeneous graphs in accordance with Eq. (1).

$$G = (V, E, X) \tag{1}$$

where V represents nodes (patients, clinicians, treatments), Edenotes interaction edges (appointments, follow-ups, treatments), and X is the node feature matrix. Each interaction between nodes is assigned a novel CRM-aware weight to reflect its importance as per Eq. (2).

$$w_{ij} = \alpha f_{freq} + \beta e^{-\lambda \Delta t} + \gamma f_{eng} \tag{2}$$

where f_{freq} represents interaction frequency, $e^{-\lambda \Delta t}$ captures recency, and f_{eng} denotes patient engagement level. The coefficients α, β, γ control the contribution of each factor. Node features are constructed by combining clinical, temporal, and behavioral attributes using Eq. (3).

$$\mathrm{x}_i = [\mathrm{x}_i^{clin} \parallel \mathrm{x}_i^{temp} \parallel \mathrm{x}_i^{beh}] \tag{3}$$

Finally, the adjacency matrix is normalized to ensure stable learning as per Eq. (4).

$$\widehat{\mathrm{A}} = \mathrm{D}^{-1/2}(\mathrm{A} + \mathrm{I})\mathrm{D}^{-1/2} \tag{4}$$

This formulation enables the PIG to effectively model both clinical relationships and CRM-driven behavioral patterns, providing a rich input representation for subsequent graph-based learning and predictive analysis.

3.3. Feature Extraction

Using the PIG as a base, the proposed system performs multi-modal feature extraction to capture complementary clinical/temporal/behavioural characteristics of patients. Let the PIG be represented as $G = (V, E, X)$, where Vdenotes nodes (patients, clinicians, treatments), Edenotes interaction edges, and $X \in \mathbb{R}^{N \times d}$ represents node features derived from CRM data.

3.3.1. Graph-Based CRM Interaction Learning

To encode relational dependencies in the PIG, a GNN with attention is employed. The node embedding at layer $l + 1$ is computed as per Eq. (5).

$$h_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij}^{(l)} W^{(l)} h_j^{(l)}\right) \tag{5}$$

where α_{ij} denotes attention coefficients capturing interaction importance, W is a learnable weight matrix, and $\mathcal{N}(i)$ represents neighboring nodes. This formulation enables the model to learn behavioral patterns such as follow-up consistency, clinician influence, and treatment adherence.

3.3.2. Temporal Patient History Modeling

Patient clinical trajectories are modelled using Bi-LSTM to capture forward and backward temporal dependencies as per Eq. (6) and Eq. (7).

$$\overrightarrow{h_t} = \mathrm{LSTM}(x_t, \overrightarrow{h_{t-1}}), \overleftarrow{h_t} = \mathrm{LSTM}(x_t, \overleftarrow{h_{t+1}}) \tag{6}$$

$$h_t^{temp} = [\overrightarrow{h_t} \parallel \overleftarrow{h_t}] \tag{7}$$

where x_t represents time-dependent clinical observations. This bidirectional representation effectively models disease progression trends and irregular visit patterns.

3.3.3. Medical Image Feature Representation

Deep spatial representations are extracted from medical images using EfficientNetV2 as per Eq. (8).

$$h^{img} = f_\theta^{EffNet}(I) \tag{8}$$

where I is the input medical image and f_θ denotes the parameterized convolutional feature extractor. This captures fine-grained pathological patterns critical for diagnosis.

3.3.4. Novel Cross-Modal Interaction Encoding

To enhance inter-modal correlation, a Cross-Modal Interaction Matrix (CMIM) is introduced as per Eq. (9).

$$M_{cm} = \tanh\left(h^{graph} W_g \cdot (h^{temp} W_t)^T\right) \tag{9}$$

where W_g and W_t are learnable projection matrices. This matrix explicitly models latent dependencies between patient behavior (CRM) and temporal clinical progression, which are often ignored in conventional frameworks.

3.3.5. Unified Multimodal Representation

Finally, all modalities are adaptively fused as per Eq. (10).

$$H_{fusion} = \mathrm{Concat}(h^{img}, h^{temp}, h^{graph}, \mathrm{vec}(M_{cm})) \tag{10}$$

This combines the previous spatial/temporal/relational representations into a single unified representation that creates a strong feature set for predicting health outcomes. At this point, we greatly enhance predictive capacity by capturing complex patterns for individual patients resulting in better accuracy and interpretability of predictive analytics within the healthcare system.

3.4. Multimodal Feature Fusion

In order to capture complex interdependencies across modalities, the heterogeneous representations image features F^{img} from EfficientNetV2, temporal features F^{temp} from Bi-LSTM, and graph-based interaction features F^{graph} from GNN are integrated through a unified transformer-based attention mechanism after the multimodal feature extraction stage. To guarantee dimensional consistency, each modality-specific feature is first projected into a shared latent space in accordance with Eq. (12).

$$\hat{F}^m = W_m F^m + b_m, m \in \{img, temp, graph\} \tag{12}$$

where W_m and b_m denote learnable projection parameters. The aligned features are then concatenated to form a multimodal embedding as per Eq. (13).

$$F^{concat} = [\hat{F}^{img} \parallel \hat{F}^{temp} \parallel \hat{F}^{graph}] \tag{13}$$

To model cross-modal dependencies, a self-attention mechanism is employed. Query, Key, and Value matrices are derived as per Eq. (14).

$$Q = F^{concat}W_Q, K = F^{concat}W_K, V = F^{concat}W_V \tag{14}$$

The attention weights are computed using scaled dot-product attention as per Eq. (15).

$$\mathrm{Attn}(Q, K, V) = \mathrm{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{15}$$

To enhance modality-specific importance, a novel adaptive modality gating function is introduced as per Eq. (16).

$$\alpha_m = \frac{\exp(\phi(\hat{F}^m))}{\sum_n \exp(\phi(\hat{F}^n))} \tag{16}$$

where $\phi(\cdot)$ is a learnable scoring function. The final fused representation is then formulated as per Eq. (17).

$$F^{fusion} = \sum_m \alpha_m \cdot \hat{F}^m + \lambda \cdot \mathrm{Attn}(Q, K, V) \tag{17}$$

where λ is a weighting factor for global attention. This gives the model an ability to adjust ratios of modalities and capture significant long-term dependencies between clinical/behavioural/temporal features together. Therefore, the result of this fusion process is a more discriminative representation which improves predictive accuracy and interpretability for downstream healthcare risk estimation tasks.

3.5. Optimization and Feature Selection

After performing multimodal feature fusion through transformers, creating a representation of high dimensionality $\mathrm{F} \in \mathbb{R}^d$ contains redundant and correlated features which impact prediction accuracy, an APSO (Adaptive Particle Swarm Optimization) technique can be applied to perform joint feature selection and hyperparameter tuning simultaneously and increase generalization capabilities of the model and improve computational efficiency of computations. APSO combines two different approaches: the behavioural patterns associated with the leadership hierarchy and encircling behaviours related to GWO (Grey Wolf Optimisation) with the aggressive nature of randomised particle optimisers (RPO). Each potential solution (agent) is a vector by Eq. (18).

$$\mathrm{X}_i = [\mathrm{S}_i, \mathrm{H}_i] \tag{18}$$

where $\mathrm{S}_i \in \{0,1\}^d$ denotes a binary feature selection mask over fused features, and $\mathrm{H}_i$represents continuous hyperparameters (learning rate, batch size, attention heads, etc.).

3.5.1. Adaptive Position Update

To balance exploration and exploitation, APSO introduces a dynamic predator coefficient $\lambda(t)$, defined as per Eq. (19).

$$\lambda(t) = \alpha \cdot \left(1 - \frac{t}{T}\right) + \beta \cdot \frac{\sigma(\mathrm{F})}{\mu(\mathrm{F})} \tag{19}$$

where t is the current iteration, $T$is the maximum iteration, and $\sigma(\cdot), \mu(\cdot)$ denote the standard deviation and mean of fused features. This term adaptively adjusts search intensity based on feature distribution. The position update is then formulated as per Eq. (20).

$$\mathrm{X}_i^{t+1} = \lambda(t) \cdot \mathrm{X}_{\text{leader}}^t + (1 - \lambda(t)) \cdot (\mathrm{X}_i^t + \gamma \cdot \Delta_i^t) \tag{20}$$

where:

- $\mathrm{X}_{\text{leader}}$represents elite solutions (analogous to alpha, beta, delta wolves),
- Δ_i^tcaptures stochastic perturbation inspired by piranha attack dynamics,
- γcontrols local exploitation strength.

3.5.2. Fitness Function (Multi-Objective)

The optimization objective jointly minimizes classification error and feature redundancy as per Eq. (21).

$$\mathcal{J} = w_1 \cdot (1 - \mathrm{Accuracy}) + w_2 \cdot \frac{\|\mathrm{S}_i\|_0}{d} \tag{21}$$

where $\| \mathrm{S}_i \|_0$ is the number of selected features, and w_1, w_2 are trade-off weights.

3.5.3. Output Integration

The optimized feature subset S^* and hyperparameters H^* are fed back into the fused representation, yielding a refined feature space as per Eq. (22).

$$\mathrm{F}^* = \mathrm{S}^* \odot \mathrm{F} \tag{22}$$

which is then used for final prediction.

3.6. Prediction and Risk Estimation

After multimodal feature fusion occurs, the next step in the proposed framework is to jointly optimise the features and predict how model generalisation will occur and ultimately provide clinically reliable results. Denote the fused features as $\mathrm{F} \in \mathbb{R}^{n \times d}$, where n is equal to total number of patients and d equals the total amount of features available for use by the model. To identify the most discriminative features and optimal hyperparameters, a hybrid APSO strategy is employed. Each candidate solution (agent) is represented as a vector $\mathrm{X}_i = [x_1, x_2, \ldots, x_d]$, where $x_j \in \{0,1\}$ indicates feature selection. The fitness of each agent is evaluated using a multi-objective function that jointly minimizes classification loss and feature redundancy as per Eq. (23).

$$\mathcal{L}_{opt} = \alpha \cdot \mathcal{L}_{cls} + \beta \cdot \left(\frac{\|\mathrm{X}_i\|_0}{d}\right) + \gamma \cdot \mathcal{R}_{corr} \tag{23}$$

where $\mathcal{L}_{cls}$ denotes prediction loss, $\| \mathrm{X}_i \|_0$ is the number of selected features, and $\mathcal{R}_{corr}$ represents inter-feature correlation penalty. The coefficients α, β, γ control the trade-off between accuracy, sparsity, and redundancy. The position update in APSO integrates exploration (inspired by GWO) and exploitation (modelled after RPO behaviour), formulated as per Eq. (24).

$$\mathrm{X}_i^{t+1} = \mathrm{X}_i^t + \lambda_1(\mathrm{X}_{best} - \mathrm{X}_i^t) + \lambda_2(\mathrm{X}_{rand} - \mathrm{X}_i^t) + \delta \cdot \nabla\mathcal{L}_{opt} \quad (24)$$

where X_{best} is the global best solution, X_{rand} introduces stochastic exploration, and δ adaptively controls convergence speed. The optimized feature subset F^* is then passed to a deep predictive model for risk estimation. The prediction task is formulated as a multi-task learning problem as per Eq. (25).

$$\hat{y}_k = \sigma(\mathrm{W}_k \cdot \mathrm{F}^* + b_k), k \in \{1,2,3\} \quad (25)$$

where $\hat{y}_1$, $\hat{y}_2$, and $\hat{y}_3$ correspond to patient risk level, disease progression, and hospital readmission probability, respectively. Here, $\sigma(\cdot)$ is the sigmoid activation for probabilistic outputs. To improve robustness, a task-adaptive weighting mechanism is introduced as per Eq. (26).

$$\mathcal{L}_{total} = \sum_{k=1}^{3} \omega_k \cdot \mathcal{L}_k, \text{where} \omega_k = \frac{1}{\log(1+\sigma_k^2)} \quad (26)$$

where σ_k^2 represents task uncertainty, allowing the model to dynamically prioritize more reliable predictions. The integration of optimisation/prediction procedures via the proposed GAMT-CARE framework allows for producing highly accurate predictions, reduced redundancy within features, and providing interpretation of those features which ultimately makes the framework ideally suited for intelligent assessment of clinical risk and supporting decisions made in healthcare settings.

3.7. Clinical Decision Support

The suggested GAMT-CARE paradigm integrates an AI-driven CDSS to convert predictive insights into practical medical decisions after the prediction and risk estimate stage. An intelligent inference module is used to further process the multimodal prediction model's outputs, which include patient risk levels, illness progression likelihood, and hospital readmission probability. This module creates individualized therapy recommendations based on patient profiles by utilizing risk stratification scores and learnt feature representations. Additionally, an early warning system is incorporated to proactively notify medical professionals about high-risk individuals, facilitating prompt medical intervention and lowering unfavorable outcomes. Additionally, the system improves resource allocation in clinical settings, schedules follow-ups, and prioritizes patient cases to deliver workflow improvement insights. Real-time patient monitoring, customized alarms, and intelligent workflow automation in clinical settings can be made possible by integrating the deployment of the suggested decision support system with platforms like Salesforce Health Cloud. The suggested paradigm supports evidence-based practice, improves clinical efficiency, and enables proactive and individualized healthcare management by combining predictive analytics with decision intelligence.

4. Result and Discussion

The Python programming environment with deep learning and data processing was used to implement the suggested GAMT-CARE framework. A multimodal healthcare dataset that included CRM-based patient interaction data, medical pictures, and EHR was used for the experimental evaluation. Standard assessment criteria, such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC), were used to evaluate the model's performance.

4.1. Dataset Collection

The MIMIC-IV Clinical Database [30], a publicly available sample version of the larger MIMIC-IV dataset, consists of electronic health records from 100 patients who were admitted to the intensive care unit (ICU) and recorded in a de-identified manner. The MIMIC-IV Clinical Database has been established as a relational database, with multiple tables representing patient records, hospital admissions, ICU stays, laboratory measurements, medications, procedures, and demographic information related to the patient population of the MIMIC-IV Clinical Database. The MIMIC-IV Clinical Database maintains the schema of the MIMIC-IV Clinical Database, making it ideal for learning the structure of a relational database and creating predictive models before you can access the full MIMIC-IV Clinical Database. To ensure compliance with privacy regulations, all sensitive patient identifiers have been removed from the MIMIC-IV Clinical Database in accordance with strict de-identified protocols. A shifted version of elapsed time is preserved in the MIMIC-IV Clinical Database, enabling you to conduct time-series analyses on temporal data such as admission date and treatment sequence. As such, the MIMIC-IV Clinical Database is useful for developing predictive models for risk prediction, patient outcome modelling, and clinical decision support, as well as for simulating CRM Distal models of interaction for follow-up patterns and visiting frequency.

4.2. Overall Comparison of Proposed and Existing Models

The suggested GAMT-CARE model considerably outperforms all baseline techniques across evaluation measures, as Table 1 shows. Its exceptional predicting capacity is demonstrated by its highest accuracy (96.84%) and AUC (0.97). Multimodal feature fusion, transformer-based learning, and optimal feature selection are credited with the improvement, which makes healthcare risk prediction more accurate and dependable.

Table 1: Proposed vs Existing Model Comparison

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
Logistic Regression	84.21	82.45	80.32	81.37	0.86
Random Forest	88.67	87.12	85.94	86.52	0.89
CNN	90.45	89.76	88.21	88.98	0.91
Bi-LSTM	91.32	90.88	89.47	90.17	0.92

GNN	92.18	91.75	90.63	91.18	0.93
Proposed	96.84	96.21	95.76	95.98	0.97

An ablation study was carried out by methodically eliminating important modules in order to assess the relevance of each element in the suggested framework. Table 2 demonstrates that performance is greatly decreased when important components are removed. The maximum accuracy (96.84%) and AUC (0.97) are attained by the whole GAMT-CARE model. This demonstrates that the total predictive performance and robustness are significantly influenced by CRM characteristics, transformer fusion, GNN, and APSO optimization.

Table 2: Ablation Study

Configuration	**Accuracy (%)**	**AUC**
Without CRM Features	92.11	0.93
Without Transformer Fusion	91.48	0.92
Without APSO Optimization	93.02	0.94
Without GNN Module	92.56	0.93
Full Model (GAMT-CARE)	96.84	0.97

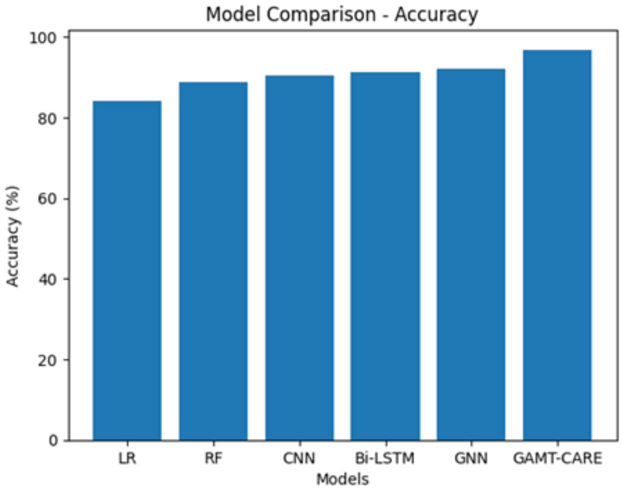

Fig 2: Accuracy Graph

The accuracy comparison between the suggested GAMT-CARE model and baseline models is shown in Fig. 2. It is clear that efficient multimodal feature integration and optimization allow the suggested framework to attain higher accuracy. Fig. 3 depicts the ROC curves for measuring how well the GAMT-CARE model performed across various points on the threshold scale. We also see that there is an acceptable balance between the true positive rate (Sensitivity) and false positive rate (<=0.05). The AUC for the GAMT-CARE ROC is determined to be 0.97, which illustrates an excellent level of classification capability when compared with baseline models. The ROC curve for GAMT-CARE maintains a position closer to the upper left corner, indicating a highly reliable means of distinguishing between high-risk and low-risk patients. This can be attributed mainly due to the combination of multimodal feature integration and the use of transformers as attention mechanisms for enhancing how these features are represented and creating decision boundaries.

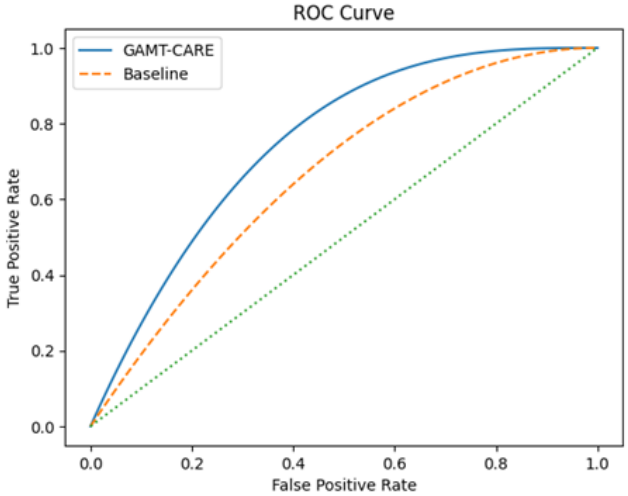

Fig 3: ROC Curve

The confusion matrix of the suggested GAMT-CARE model for patient risk classification is displayed in Fig. 4. Only a small percentage of instances (30 false positives and 25 false negatives) are incorrectly classified by the algorithm, which accurately diagnoses 920 low-risk and 1025 high-risk patients. The significant predictive capacity and dependability of the suggested framework are demonstrated by the large number of true positives and true negatives. Together, the experimental findings, comparison analysis, and ablation study show that the suggested GAMT-CARE framework successfully integrates multimodal healthcare data and sophisticated optimization techniques to attain higher prediction accuracy and robustness.

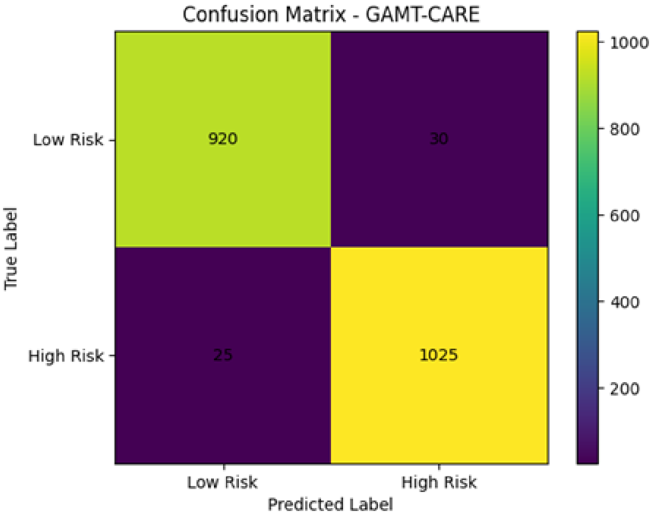

Fig 4: Confusion Matrix for GAMT-CARE

5. Conclusion

This new study introduces a smart healthcare model called GAMT-CARE, which combines predictive healthcare and artificial intelligence (AI) for managing clinical workflow processes. A cognitive model (PIG) was developed to show

how patients, doctors, treatment plans, and follow-up communications are related and connected through the customer relationship management system (CRM) used in the study. To analyze the complex and varied types of healthcare data collected for the study appropriately, a GAMTNet Hybrid DL Architecture was applied to the data collected in the study. The clinical image data were extracted using the EfficientNetV2 architecture, patient history data were extracted using Bi-LSTM, and the customer relationship management communications data were extracted using GNN to create multimodal representations of the data that directly relate to the clinical domain. An attention mechanism based on transformer architecture was used to combine these different types of models to build a complete model with respect to all three domains and represent all of the model parameters appropriately in order to model the entire data source as an integrated whole. In addition to using the attention mechanism to improve the overall performance of the GAMT model, a hybrid particle swarm optimization-based optimization methodology using an APSO algorithm was applied to provide an effective means for selecting the most appropriate features and performing the necessary hyperparameter optimization for the GAMT model. Together, the GAMT model allowed early prediction of patient risk, disease trajectory, and likelihood for hospital readmission, which leads to improved optimization of intelligent clinical workflows and tailored healthcare intervention of individual health. The GAMT model achieved an overall accuracy rate of 96.84%.

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