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Predicting Diabetic Distress and Emotional Burden in Type-2 Diabetes Using Explainable AI

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ABSTRACT Diabetic distress is a significant psychological burden affecting many individuals with Type-2 Diabetes Mellitus. Despite its prevalence, it remains underrecognized, and its impact can be complex. This study explores the integration of multimodal data sources and machine learning to identify diabetic distress and emotional burden in patients with Type-2 Diabetes Mellitus. The study highlights the use of Explainable Artificial Intelligence to make predictions more transparent. It combines patient information like age, gender, laboratory results, and survey scores to train and compare machine learning methods. Models tested include Ridge regression, Lasso regression, linear and logistic regression, neural networks, support vector machines, random forests, and various boosting techniques. Among all of these, Extreme Gradient Boosting with SHapley Additive exPlanations delivered the best results. It was 96.14% accurate, 0.94 precise, had an ROC-AUC of 0.98, an F1-score of 0.95, and a recall of 0.95. The approach also generates explanations of why a specific prediction is being generated. For instance, it shows how specific blood glucose levels or distress subscale scores influence the predicted emotional load. These clear explanations enable clinicians to make sense of both the model's performance and the reasoning behind it. Such transparency is critical to the building of trust in machine learning–based decision support systems for diabetes care.tors influencing DDS.

INDEX TERMS Clinical Decision Support, Diabetic Distress (DDS), Explainable AI (XAI), Machine Learning (ML), Multimodal Data Analysis, SHapley Additive exPlanations (SHAP), Type-2 Diabetes Mellitus (T2DM), XGBoost.

I. INTRODUCTION

DIABETES mellitus is a widespread metabolic condition that affects millions worldwide and demands ongoing medical attention and self-management [1]. Beyond the physical challenges, many individuals experience a form of psychological strain known as diabetic distress, which involves feelings of helplessness, emotional pressure, and frustration related to disease management [2]. This distress can significantly reduce quality of life and worsen health outcomes, often leading to more complications, poor blood sugar control, and skipped treatments. Because current tools are limited in identifying at-risk patients, diabetic distress frequently remains undetected and untreated, even though it plays a crucial role in patient well-being and long-term disease management [3].

It was approximated by the World Health Organization in 2022 that between 36 to 45 percent of individuals living with Type-2 diabetes experience diabetic distress, and it is gender-based [4]. It has been proven that women experience more distress because they have work demands as well as emotional demands, while men, who experience less distress, experience a higher rate of mortality due to the complications brought [5]. This disparity points to the importance of interventions and forecasting tools that address the specific challenges that each gender encounters in handling diabetic distress [6].

Existing approaches to identifying diabetic distress have several weaknesses. Many studies use traditional techniques, such as statistical tests and survey responses, but these methods often rely on data collected at a single point in time, involve relatively few participants, and may not represent a broader population [7]. The methodologies employed provide only a superficial understanding of the temporal progression of distress levels and the interplay among behavioral, emotional, and clinical variables that influence distress outcomes [8]. In addition, most current models function as "black boxes" with little transparency, which makes them difficult to trust in clinical practice where understanding the basis for a prediction is crucial for treatment decisions [9].

Despite these efforts, significant gaps still exist in the literature. First, many existing studies on diabetic distress rely on single-modality datasets either clinical measures or survey responses and often draw from small, homogenous cohorts, limiting their ability to capture the multifaceted interplay of demographic, clinical, and psychological factors in a broader Type-2 diabetic population. Second, prior work typically focuses on either continuous distress scores (regression) or categorical severity levels (classification) in isolation, leaving clinicians without a unified tool that provides both a quantitative Total DDS Score and an actionable severity category (low, moderate, high). Third, although some researchers have employed powerful "black-box" algorithms, they rarely incorporate Explainable Artificial Intelligence techniques, so healthcare providers cannot discern which specific features such as fasting blood sugar or emotional burden subscale values drive each prediction. Finally, feature-selection and preprocessing methods in previous studies are often limited to basic imputation and scaling, lacking rigorous statistical validation and domain expert review to ensure that the most clinically relevant predictors are retained. Together, these shortcomings underscore the necessity of a comprehensive, multimodal framework that combines robust feature engineering with an Extreme Gradient Boosting model and SHapley Additive exPlanations, thereby delivering both high predictive performance and transparent, patient-specific insights for early intervention and personalized care in Type-2 diabetes.

Machine learning provides the means to sidestep many of these problems by looking at large, varied data sets to find patterns that are not apparent to traditional approaches [10]. With machine learning algorithms, you can predict levels of distress by combining various types of data, such as patient demographics, clinical information, and psychological testing [11]. Incorporating Explainable AI techniques makes it even clearer by determining particular factors that decided each prediction, making the outcome more credible to patients and doctors alike [12].

Explainable AI is crucial in determining distress and psychological burden in Type-2 diabetes. Techniques like SHapley Additive exPlanations (SHAP) uncover features that motivate distress predictions [13]. For instance, SHAP can indicate the contribution of diabetes duration, age, emotional burden, or fasting blood sugar (FBS) levels to the patient's distress severity [14].

High interpretability is particularly crucial when clinical and psychological factors intersect in intricate ways. By revealing such connections, XAI enables healthcare practitioners to develop interventions that suit the unique circumstances of each patient [15]. It also informs patients about their own level of distress and what matters to them most, motivating improved self-care and treatment compliance. The primary objective of this research is to design an appropriate machine learning system that precisely detects distress levels and severity among Type-2 diabetic patients. The system draws upon a variety of types of data, including demographic, clinical, and psychological data, to incorporate numerous factors affecting distress. At the same time, XAI methods help ensure that predictions are clear and easy to understand. What makes this study unique is the creation of a risk stratification system that can be used in clinical settings. This could help doctors identify distress early on and adjust their treatments to meet individual needs. The main goals of this research are:

- Preprocess and organize multimodal data by handling missing values, removing outliers, and addressing multicollinearity, while ensuring that numerical and categorical features remain consistent.
- In order to choose the most relevant features and enhance the accuracy of predictions, there is a need to utilize strict feature engineering methods. Some of the methods involved include correlation analysis, risk flagging, ANOVA, and chi-square tests, together with the inclusion of interaction terms. Through the application of these approaches, the effectiveness of the predictive model will be greatly improved.
- Assess the performance of various machine learning algorithms using robust metrics that emphasize both predictive accuracy and clinical usefulness.
- Create a strong machine learning system that can recognize levels of distress in diabetes and sort them by severity using both regression and classification methods.
- Incorporate Explainable AI methods such as SHAP to make the model's predictions transparent and to provide actionable insights for clinical decision-making.

This study shows that XAI helps the ML framework not just by making it more accurate, but also by making the predictions clearer and easier to use.By integrating XAI into the predictive workflow, this approach guarantees that the outputs are clinically meaningful. It also assists healthcare providers in assessing risk severity in patients, initiating timely care, and delivering personalized interventions with confidence. Ultimately, XAI bridges the gap between advanced AI methodologies and their real-world applications, improving patient outcomes in the management of diabetic distress.

The remainder of this paper is organized as follows. Section 2 reviews related work on machine learning approaches to psychological outcomes in diabetes and highlights their limitations. Section 3 details our proposed methodology, including dataset description, exploratory data analysis, data preprocessing, feature engineering, definition of prediction tasks, model development, validation strategy, and Explainable AI integration. Section 4 presents experimental results, comparing performance across regression and classification models and providing SHAP-based interpretability analysis. Finally, Section 5 concludes the study by summarizing key findings, discussing clinical implications, and suggesting directions for future research.

II. RELATED WORKS

The connection between diabetes and psychological distress, including depression, has been extensively studied in the context of predictive methods using Machine Learning (ML). Various approaches have been explored to leverage Electronic Health Records (EHRs), survey data, and physiological measurements for detecting high-risk individuals. This section reviews recent research, focusing on their methodologies, algorithms, findings, and limitations.

The study [16] analyzed the severity levels of anxiety, depression, and stress in individuals using machine learning algorithms. Researchers collected data from 348 patients aged 20-60 years and categorized them into five severity levels using the Depression, Anxiety, and Stress Scale (DASS-21) questionnaire. The dataset was split into 70% training and 30% testing sets, and five machine learning models such as Decision Tree, Random Forest, Naïve Bayes, Support Vector Machine (SVM), and k-Nearest Neighbors (k-NN) were applied. We evaluated the performance by using measures based on the confusion matrix. Random Forest outperformed other models for stress prediction with an F1-score of 0.711, while Naïve Bayes exhibited the highest accuracy (85.5%) and F1-score (0.836) for depression classification. However, limitations included a small sample size, reliance on self-reported data, and the lack of external validation, restricting broader applicability.

A subsequent study [17] focused on forecasting specialized severity levels (normal, mild, moderate, severe, extremely severe) of anxiety, depression, and stress using hybrid classification approaches. The dataset was partitioned into training (75%) and testing (25%) sets, and five-fold cross-validation was employed. Eight machine learning models, including Naïve Bayes, k-NN, Random Forest, and Radial Basis Function Network (RBFN), were deployed alongside a hybrid classifier combining K-Star and Random Forest. The RBFN model demonstrated the highest efficiency with more accuracy 96% and a near perfect ROC-AUC score. The hybrid strategy further improved accuracy for anxiety classification in the DASS-42 dataset, achieving 92.15% accuracy. However, limitations included class imbalance, computational inefficiency of hybrid methods, and limited dataset versatility.

An automated screening system [18] was developed to detect anxiety and depression among shipboard workers using machine learning models. Recursive Feature Elimination (RFE) retained 14 predictors for optimal accuracy. Five machine learning models were evaluated: Logistic Regression, Naïve Bayes, Random Forest, SVM with an RBF kernel, and CatBoost. Results showed that CatBoost outperformed all other models, achieving 89.3% precision, an AUC of 0.882, and 78.6% recall using Random Forest. The study highlighted the effectiveness of automated ML-based mental health assessments in occupational health. However, limitations included a small dataset, class imbalance, and restricted generalizability to other populations.

A study [19] utilized auto-machine learning (AutoML) techniques to develop predictive models for severe psychological distress. Statistical tests such as chi-square and t-tests were used to identify significant predictors, while the Synthetic Minority Oversampling Technique (SMOTE) was applied to address class imbalance. Among five traditional ML algorithms, Auto-GBM achieved the best performance with a precision of 89.75%, an F1-score of 89.48%, and an AUC of 95.57%.

Another study [20] explored predictive modeling for diabetes classification using the Pima Indian Diabetes dataset. The authors applied feature selection using the Boruta wrapper algorithm, k-NN imputation for missing values, and outlier removal. Five supervised learning algorithms SVM with a linear kernel, RBF Kernel SVM, k-NN, Artificial Neural Network (ANN), and Multifactor Dimensionality Reduction (MDR) were tested. Among them, k-NN achieved the highest AUC (0.92) and excelled in recall (0.90) and F1-score (0.88), while SVM-linear attained optimal precision (89%). Limitations included an imbalanced dataset affecting generalizability and the absence of external validation.

A study [21] developed predictive models for detecting depression in individuals at risk or living with diabetes using electronic medical records. Missing data was handled using Multiple Imputation by Chained Equations (MICE), and class imbalance was addressed with SMOTE and Tomek Links. Six ML models named as Logistic Regression, Naïve Bayes, Random Forest, AdaBoost, XGBoost, and ANN were applied with hyperparameter tuning via grid search. SHAP analysis was used to interpret predictor importance, identifying factors such as sex, age, osteoarthritis diagnosis, BMI, and A1C levels. XGBoost achieved the highest performance with an AUC of 0.70 and an F1-score of 0.73. However, limitations included a lack of demographic diversity and reliance on cross-sectional data..

The study [22] applied machine learning techniques to predict stress levels during the COVID-19 pandemic. Feature selection used Correlation-Based Feature Selection (CFS), and four ML models—Logistic Regression, SVM, Naïve Bayes, and Random Forest—were evaluated using precision, recall, F1-score, and AUC. Logistic Regression performed best with an AUC of 0.782 and sensitivity above 75%. Key stress predictors included emotional stability, positive coping strategies, internal locus of control, and income levels. However, sample bias from online recruitment and limited longitudinal data were noted as limitations.

Recent advances have also demonstrated the power of combining Extreme Gradient Boosting with SHapley Addi-

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tive exPlanations (SHAP) and related hybrid optimization methods in both medical and non-medical domains. Researchers in [23] optimized LSTM network weights via a modified metaheuristic algorithm and achieved high classification accuracy for Parkinson's detection; while not using XGBoost directly, this work illustrates how metaheuristic-guided model tuning can significantly boost performance and interpretability in health-related time-series tasks.

In [24] a hybrid pipeline first applied a bespoke crayfish optimization to tune CNN hyperparameters, then employed AdaBoost and XGBoost as ensemble learners reporting over 95 percent classification accuracy on multiple waste datasets and leveraging SHAP for feature importance analysis. Similarly, in [25] the researchers demonstrates that a metaheuristic-optimized XGBoost model, interpreted with SHAP, can uncover key pollutant drivers, achieving over 93 percent predictive accuracy on atmospheric chemistry benchmarks. In [26] the authors demonstrated how hybridizing a firefly optimization algorithm with an extreme learning machine (ELM) yields state-of-the-art results across diverse medical datasets. This highlights the combining metaheuristic feature selection with explainability tools (analogous to SHAP) provides actionable insights for clinicians.

Finally, researchers [27] developed a Depression and Anxiety Prediction (DAP) model to address fragmented and heterogeneous EHR data in Type 2 Diabetes Mellitus (T2DM) patients. The model employed contrastive pretraining (DAPCP) to integrate structured and unstructured EHR data and fine-tuning (DAPFT) for supervised prediction. Preprocessing included imputing missing values, normalizing structured data, and vectorizing unstructured text using Term Frequency-Inverse Document Frequency (TFIDF). The DAP model performed better than Logistic Regression, Random Forest, and Extreme Gradient Boosting, with an ROC-AUC of 0.916 and a PR-AUC of 0.806. However, this study did not include hierarchical diagnosis modeling and was based on regional datasets.

Review of related studies [16]- [27]identifies a few weaknesses in existing research. One of the significant concerns is that most predictive models are "black boxes" with limited explanation of their reasoning and reduced clinical utility. Another weakness is that studies frequently employ data from particular locations, which may lead to biases and diminish the model's applicability to other populations. Furthermore, very few studies make the best use of sophisticated feature engineering methods, and merging various sources of data, including demographic, clinical, and psychological data, is an area that has not been addressed yet. In a bid to fill the gaps, this paper introduces a novel machine learning paradigm for forecasting the severity of diabetic distress among Type-2 diabetic patients. By using Explainable AI methods like SHapley Additive exPlanations (SHAP), our approach ensures that each prediction can be explained in terms of specific patient features, making the results actionable for physicians. The framework also merges multimodal data sources and applies advanced feature engineering to improve model accuracy and overall performance.

III. METHODOLOGY

This study utilizes advanced methods like Explainable AI, combined data preprocessing, and field-dependent feature engineering to predict diabetic distress. It incorporates both regression and classification models to give an interpretable framework for the estimation of distress scores and reasons of emotional burden among Type-2 diabetic patients.The inclusion of SHapley Additive exPlanations (SHAP) [28] provides transparency so that clinicians can view precisely which patient features are responsible for each prediction. This method not only seeks correct estimation of distress scores but also offers actionable information as to why one patient is experiencing greater emotional burden, a significant advancement in being able to handle psychological aspects of diabetes.

As shown in Figure 6, the methodology follows these sequential steps: Diabetes Distress Scale 17 (DDS17), Dataset, Exploratory Data Analysis (EDA), Data Preprocessing, Feature Engineering, Defining Prediction Tasks, Model Development, Data Splitting and Validation, Explainable AI (XAI) Integration, Proposed XAI-XGBoost-SHAP Algorithm, and Experimental Setup. Each of these subsections corresponds to one block in the pipeline, providing a clear, step-by-step progression from clinical scoring through data preparation, model training, interpretability analysis, and experimental validation.

A. DIABETES DISTRESS SCALE 17 (DDS17)

The Diabetes Distress Scale (DDS17) is a popular instrument for measuring the emotional and psychological burden of patients with diabetes. The Diabetes distress is measured on 17 items which cover various domains of diabetes care, such as emotional burden, distress related to the physician, regimen-related distress, and interpersonal distress. Every item is measured using a 6-point Likert scale in which patients report how much distress they feel for each statement:

- **1** - Not a Problem
- **2** - A Slight Problem
- **3** - A Moderate Problem
- **4** - Somewhat Serious Problem
- **5** - A Serious Problem
- **6** - A Very Serious Problem

To calculate the total DDS score, the responses to all 17 questions are added together and then divided by 17 to produce an average. A higher mean reflects more overall distress. A mean of 3 or above points towards clinically significant distress and requires further intervention. DDS17 has four subscales, each assessing a different aspect of distress:

1) **Emotional Burden**: Evaluates feelings of frustration, fear, depression, and emotional discomfort related to diabetes.
   - Score ≤ 2: No significant emotional burden.
   - Score 2.1 - 2.9: Mild emotional burden.

- Score ≥ 3: Significant emotional burden.

2) **Physician-Related Distress**: Measures distress related to interactions with healthcare providers, including concerns about care and communication.
   - Score ≤ 2: No significant issues with healthcare providers.
   - Score 2.1 - 2.9: Mild distress in physician-related matters.
   - Score ≥ 3: Significant distress related to healthcare providers.
3) **Regimen-Related Distress**: Assesses distress associated with diabetes management routines, including blood sugar monitoring, diet, and medication adherence.
   - Score ≤ 2: No significant regimen-related distress.
   - Score 2.1 - 2.9: Mild regimen-related distress.
   - Score ≥ 3: Significant regimen-related distress.
4) **Interpersonal Distress**: Evaluates distress related to social and family support.
   - Score ≤ 2: No significant interpersonal distress.
   - Score 2.1 - 2.9: Mild interpersonal distress.
   - Score ≥ 3: Significant interpersonal distress.

A score of 3 or more on the total DDS or any subscale is a measure of severe distress and merit further assessment or treatment. For our purposes, machine learning algorithms set these DDS17 scores as target outcomes to predict both the level of distress and severity. Grasping the clinical relevance of such scores enables us to optimize models for the rapid identification of at-risk patients to permit timely and individualized care. In this research, the models utilize overall DDS scores as well as subscale scores as direct targets to sort patients into low, moderate, or high distress groups. Such a setup provides informative results on the emotional and psychological issues of Type-2 diabetic patients. By distinctly characterizing these categories and pointing out areas calling for clinical attention, our methodology ensures that predictions are transparent and informative for healthcare practitioners. Incorporating Explainable AI techniques further improves model clarity, making it easier for clinicians to trust and act on the results, ultimately leading to better patient outcomes.

B. DATASET

This part explains where the patient data comes from and how it is organized for use in regression and classification tasks. It also enumerates significant demographic, clinical, and psychological characteristics and gives summary statistics that unveil the cohort's profile following cleaning and outliers' removal. The dataset [29] comprises 250 Type-2 diabetic patients and contains a range of features to predict diabetes distress and emotional burden. Each entry is for a single patient and holds extensive demographic, lifestyle, and diabetes-related data. The dataset is structured to support both regression and classification tasks for predicting distress scores and severity levels.

- Age Range: 35 to 86 years, with a mean age of approximately 58 years.
- Distress Scores: Emotional Burden, Physician-Related Distress, Regimen-Related Distress, and Interpersonal Distress scores range from 1.0 to 5.0.
- Total DDS Score: Ranges from 1.1 to 5.0, with a mean around 2.5.

Our final dataset comprises 232 Type-2 diabetes patients after data cleaning (from an initial 250, a reduction of 7.2% due to missing values or outlier removal), which, while modest, reflects a clinically relevant cross-section of our institution's patient population in terms of age (mean 52.75 $\pm$ 9.72 years), gender (34% male, 66% female), and clinical profiles (fasting blood sugar mean 164.5 $\pm$ 55.18 mg/dL). To mitigate overfitting risks associated with smaller cohorts, this work employed stratified 5-fold cross-validation ensuring that each fold retained approximately 46 or 47 patients with proportional representation of low, moderate, and high distress levels and averaged performance metrics across folds. Furthermore, rigorous feature engineering reduced the feature set to the 12 most predictive variables, thereby minimizing model variance. It also leveraged Extreme Gradient Boosting an ensemble algorithm known to reduce overfitting by combining M learners (M = 100 trees in our optimal configuration) through gradient-based residual fitting further enhancing model stability. Nonetheless, the generalizability beyond our cohort will require additional validation: future work will involve collecting data from multiple centers to increase N substantially and applying transfer learning or domain adaptation techniques to ensure that the XGBoost-SHAP model maintains performance across diverse populations. Table 1 provides a statistical summary of key dataset features.

C. EXPLORATORY DATA ANALYSIS

In this sub-section, statistical and graphical methods are employed to determine patterns, relationships, and outliers within the data. Correlation matrices, scatter plots, and distribution tests guide feature selection and model building. Exploratory Data Analysis (EDA) is an important step for interpreting dataset structure. It employs methods that identify patterns, relationships, and outliers and also verify data quality and missing values. In this investigation, the EDA emphasizes these major goals:

1) Identify Target Variables

The initial task in EDA is to figure out what we want to predict. For regression, the main target is the Total DDS Score, which indicates the overall degree of diabetic distress. From that score, we define severity levels (low, moderate, or high distress) to group patients according to their risk. Clearly specifying these targets ensures that feature selection and model development steps remain focused on the intended prediction goals.

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TABLE 1. Statistical Analysis of the Dataset

Feature Name	Feature Type	Mean	Median	Mode	Std. Dev.	Skewness	Min	Max	Conf. Level (95%)	P-Value
Age	Numerical	52.75	53	60	9.72	0.00021	28	79	1.21	<0.001
Gender (Male=80)	Categorical	53.96	52.5	50	10.65	0.16789	31	79	0.05	<0.001
Gender (Female=170)	Categorical	52.12	53	60	9.23	-0.16850	28	76	1.21	<0.000
Weight	Numerical	62.15	60	60	10.24	0.97292	37	110	1.27	<0.001
Occupation	Categorical	-	-	Worker	-	-	-	-	-	-
Smoking	Categorical	-	-	No	-	-	-	-	-	-
Alcohol	Categorical	-	-	No	-	-	-	-	-	-
Caffeine	Categorical	-	-	Yes	-	-	-	-	-	-
Marital Status	Categorical	-	-	Married	-	-	-	-	-	-
Food Type	Categorical	-	-	Mixed	-	-	-	-	-	-
Disease Since	Continuous	63.3	36	24	62.3	1.54	1	348	7.74	<0.001
FBS (Fasting Blood Sugar)	Continuous	164.5	158	140	55.18	1.08	70	372	6.86	<0.001
PPBS (Postprandial Blood Sugar)	Continuous	255.0	239	230	81.76	0.74	90	587	10.16	<0.001
Emotional Burden	Continuous	2.00	1.80	2	0.78	0.98	1	4.6	0.10	<0.001
Physician Related Distress	Continuous	1.81	1.00	1	0.60	4.64	1	4.75	0.08	<0.001
Regimen Related Distress	Continuous	1.72	1.60	1	0.75	1.45	1	4.60	0.09	<0.001
Interpersonal Distress	Continuous	1.28	1.00	1	0.73	3.23	1	5	0.09	<0.001
Total DDS Score	Continuous	1.60	1.40	1.40	0.60	2.00	1	4.60	0.07	<0.001

2) Explore Relationships

Exploring the relationships among various features and target variables is an essential step in data analysis. In this study, the primary target variables are:

- Total DDS Score (used for regression)
- Severity Levels (used for classification)

To analyze how the features influence these target variables, we use correlation analysis and visualizations, such as scatter plots and heatmaps, as shown in Figure 1 and Figure 2.

D. DATA PREPROCESSING

This part talks about how we keep data consistent, handle missing values, and prepare features for machine learning by normalizing or encoding them. Techniques such as mean or median imputation, KNN imputation, outlier detection, and categorical encoding are used to prepare the dataset for reliable modeling. Preparing the data is really important to keep the dataset tidy, uniform, and set for analysis. The fundamental objective of data preprocessing is to modify raw data into a format that machine learning models can use efficiently. Below are the significant stages involved in the data preprocessing process for this work:

1) Data Consistency

Ensuring that the dataset is consistent in terms of data types, formats, and scales is fundamental for downstream analysis. This involves:

- Verifying consistency in feature types: ensuring numerical features (e.g., Age, FBS, PPBS) are accurately formatted and categorical features (e.g., Gender, Occupation) are represented as strings or integers.
- Securing uniformity in measurement units, particularly for Age, FBS, and PPBS, where consistency is crucial for accurate calculations and comparisons.

The data types for all features were validated, and no issues were found regarding format consistency.

2) Handling Missing Data

Missing data can introduce bias, reduce model effectiveness, and lead to incorrect inferences. Various imputation methods were applied based on the nature of the feature:

- For numerical features like Age, FBS, and PPBS, missing values were imputed using statistical methods such as mean or median.
- Mean imputation is defined as:

$$X_{\text{mean}} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{1}$$

where X_i represents observed values, and n is the total number of non-missing values.

- If the data distribution is skewed, the median is used as a more robust measure:

$$X_{\text{median}} = \text{median}(X) \tag{2}$$

- The **K-Nearest Neighbors (KNN) imputation** method estimates missing values based on the values of the nearest neighbors using the equation:

$$\hat{x}_i = \frac{1}{K} \sum_{j \in N_i} x_j \tag{3}$$

where N_i represents the set of K nearest neighbors to x_i.

After applying these imputation methods and eliminating rows with missing categorical values, Table 2 summarizes the improvements.

TABLE 2. Analysis of Handling Missing Data Approach

Feature Name	Missing Rows	Imputation Method	Action
Age	15	Mean	Mean value of Age
FBS	20	Median	Median value of FBS
PPBS	10	KNN	KNN-imputed value
Gender	5	Removal	Dropped rows
Occupation	3	Removal	Dropped rows

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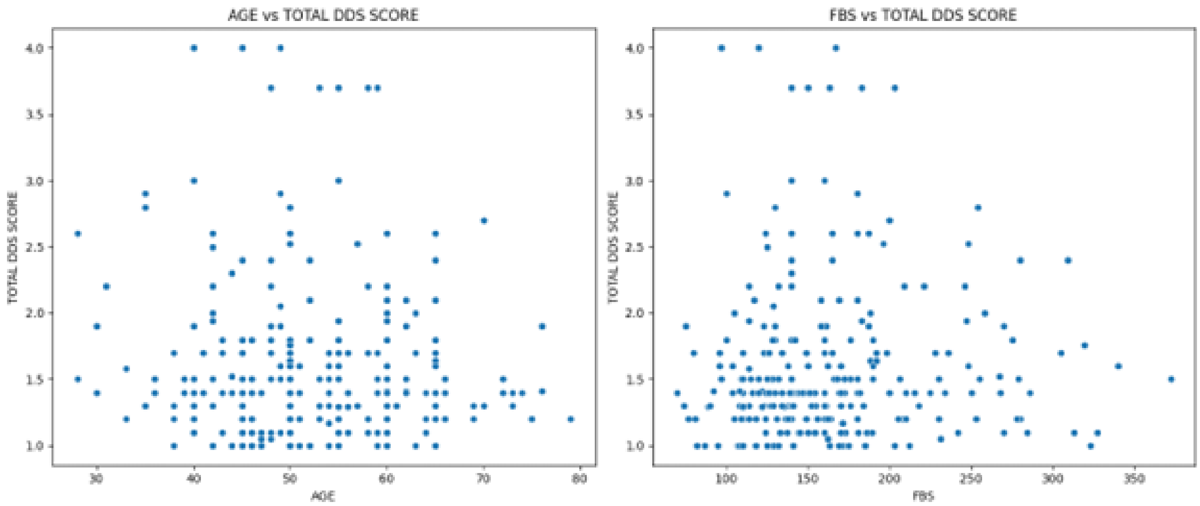

FIGURE 1. Scatter plot showing the relationship between Age and Total DDS Score, and FBS and Total DDS Score.

After performing imputation and elimination, the dataset now contains 242 rows (reduced from the initial 250 rows).

3) Normalization

Normalization ensures numerical data is scaled to a specific range, typically [0,1], enhancing performance and convergence speed in machine learning algorithms. In this study, Min-Max Scaling was used:

$$X_{\text{norm}} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{4}$$

where X represents the original feature value, and $\min(X)$ and $\max(X)$ are the minimum and maximum values of the feature. This method was applied to Age, FBS, and PPBS. Table 3 presents a sample output.

TABLE 3. Sample Output of Min-Max Scaling Technique

S. No	Age	Age (Norm)	FBS	FBS (Norm)	PPBS	PPBS (Norm)
1	39	0.35	109	0.14	129	0.12
2	48	0.53	162	0.34	289	0.38
3	49	0.56	129	0.18	220	0.26
4	47	0.51	231	0.50	375	0.50
5	54	0.71	171	0.28	245	0.24

These normalized features are now ready for training and testing machine learning models.

4) Handling Outliers

Outliers can distort machine learning results. Interquartile Range (IQR) and Z-score methods were used to detect and manage outliers in features such as Age, FBS, PPBS, Weight, and Disease Since.

The Z-score is calculated as:

$$Z = \frac{X - \mu}{\sigma} \tag{5}$$

where X is the data point, μ is the mean, and σ is the standard deviation.

The Interquartile Range (IQR) is defined as:

$$IQR = Q3 - Q1 \tag{6}$$

where $Q1$ and $Q3$ represent the 25th and 75th percentiles, respectively.

Boxplots and histograms before and after outlier handling are shown in Figure 3.

After handling outliers and eliminating rows with missing data, the dataset has been updated to 232 rows. These changes are summarized in **Table 4.

TABLE 4. Summary of Changes by Handling Outliers

Feature Name	Handling Outlier	Before	After
Age	15 missing values	12 outliers removed	3 rows dropped
FBS	20 missing values	15 outliers removed	5 rows dropped
PPBS	10 missing values	8 outliers removed	2 rows dropped
Gender	0 missing values	No outliers	No action required
Occupation	0 missing values	No outliers	No action required
Marital Status	0 missing values	No outliers	No action required

5) Feature Encoding

Many machine learning algorithms require numerical input; thus, encoding categorical features is a critical step. The dataset used in this study includes categorical variables such as **Caffeine, Alcohol, Gender, Smoking, Occupation, and Marital Status**. By encoding these variables, they can be transformed into a format suitable for the models.

Two encoding techniques were used:

- **Label Encoding**: Assigns a unique numerical value to each category.
- **One-Hot Encoding**: Converts categorical variables into binary values (0 or 1).

Table 5 provides an overview of the feature encoding techniques applied.

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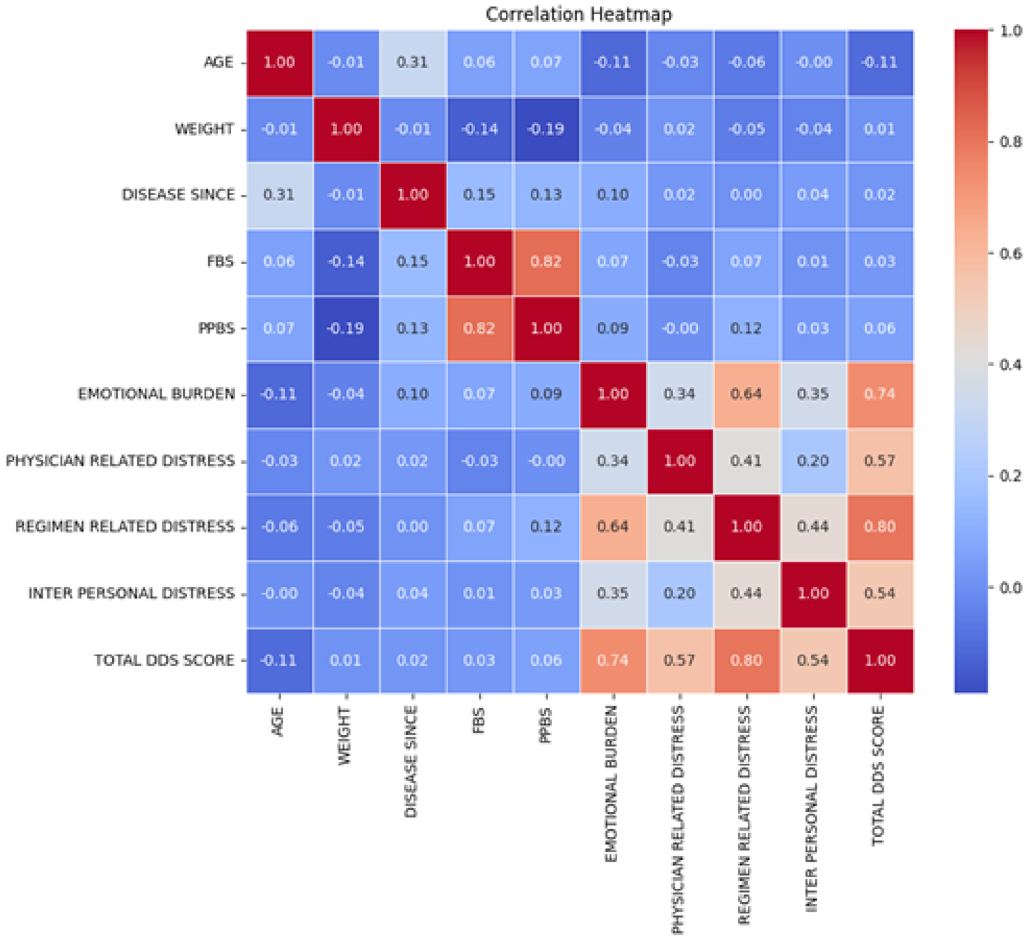

FIGURE 2. Heatmap showing correlations among continuous features in the dataset.

TABLE 5. Feature Encoding for Categorical Features

Feature Name	Encoding Method	Categories	Encoded Values
Gender	Label Encoding	Male, Female	0: Male, 1: Female
Occupation	One-Hot Encoding	Employed, Unemployed, Student, etc.	1 for each category, 0 otherwise
Marital Status	Label Encoding	Yes, No	0: No, 1: Yes
Smoking	Label Encoding	Yes, No	0: No, 1: Yes
Alcohol	Label Encoding	Yes, No	0: No, 1: Yes
Caffeine	Label Encoding	Yes, No	0: No, 1: Yes
Food Type	Label Encoding	Veg, Mixed	0: Veg, 1: Mixed

Binary features such as Marital Status, Gender, Alcohol, Smoking, Food Type, and Caffeine were processed using Label Encoding, representing 'Yes' as 1 and 'No' as 0. For multi-category features like Occupation, One-Hot Encoding was applied to create separate binary columns for each category.

E. FEATURE ENGINEERING

This sub-section discusses how to identify and select the most helpful features for distress score and severity level prediction. Methods like Pearson and Spearman correlation, chi-square tests, and ANOVA analyses are used to find and keep features strongly correlated with the target variables. Feature engineering is an important step for enhancing model performance. It constitutes generating new features out of available data, selecting the most appropriate ones, and reshaping them to optimize model precision. In this paper, we employ a combination of feature engineering methods to more accurately predict both the Diabetic Distress Scale (DDS) Score as well as the corresponding severity levels.

1) Correlation Analysis

An important part of this research is looking at correlation analysis. The goal here is to explore the emotional burden and diabetic distress experienced by patients with Type-2 diabetes. The intention is to find multicollinearity between numerical features and quantify the correlation of each feature with the ultimate target variable, Total DDS Score. Highly correlated features can introduce redundancy and degrade model performance.

This step evaluates correlation using both:

- Pearson correlation (r): Measures linear relationships.
- Spearman correlation (ρ): Measures monotonic relationships.

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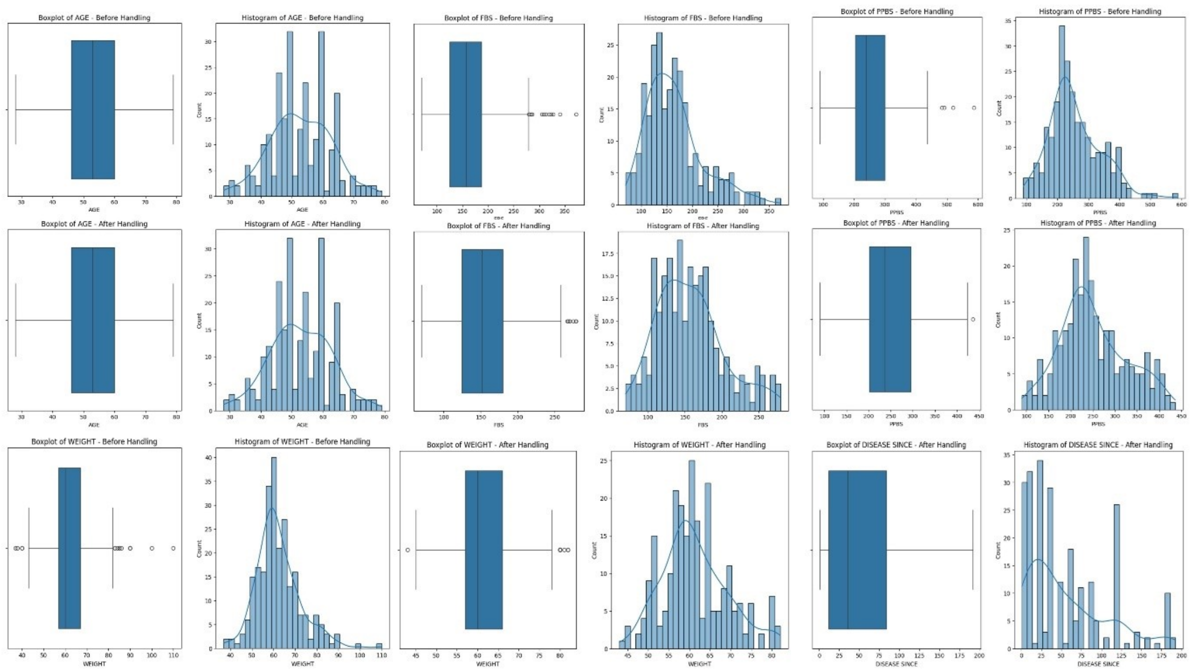

FIGURE 3. Boxplots and histograms before and after outlier handling.

The mathematical formula for Pearson correlation coefficient (r) is given in Equation (7):

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{7}$$

where:

- x_i, y_i are individual data points for two features.
- $\bar{x}, \bar{y}$ are the mean values of the two features.
- n is the total number of data points.

The Spearman correlation coefficient (ρ), which is based on ranked data rather than raw values, is given in Equation (8):

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{8}$$

where:

- d_i represents the difference between ranks of corresponding values.
- n is the number of observations.

Features with a correlation coefficient $r > \pm 0.85$ were flagged for redundancy. The results of the correlation analysis are summarized in Table 6.

TABLE 6. Outcomes of Correlation Analysis

Feature Pair	Correlation Type	Value	Action
FBS vs PPBS	Pearson (r)	0.77	Retained both
Emotional Burden vs Total DDS Score	Pearson (r)	0.74	Retained both
Physician Distress vs Regimen Distress	Spearman (ρ)	0.66	Retained both
Interpersonal Distress vs Total DDS Score	Pearson (r)	0.81	Retained both
Disease Since vs Age	Spearman (ρ)	0.80	Retained both

2) Chi-Square Analysis

The Chi-Square Analysis evaluates the relationships between categorical features and the target variable (Total DDS Score). By determining whether these categorical variables significantly affect the outcome, we can identify which features should be retained and which can be removed.

To conduct this analysis, categorical features such as Age, Gender, Marital Status, Occupation, Caffeine, Alcohol, Smoking, and Food Type were considered. For each categorical feature, the Chi-Square statistic and corresponding p-value were calculated to assess the significance of its relationship with Total DDS Score.

The significance level ($\alpha = 0.05$) was used to determine whether to reject the null hypothesis. If the p-value is less than 0.05, we reject the null hypothesis, indicating that the feature significantly impacts the target variable. The results are summarized in Table 7.

TABLE 7. Results of Chi-Square Analysis

Feature Name	Chi-Square	P-value	Degrees of Freedom	Action
Gender	5.12	0.023	1	Retained
Occupation	1.86	0.172	2	Dropped
Smoking	6.45	0.011	1	Retained
Alcohol	0.78	0.377	1	Dropped
Caffeine	3.56	0.059	1	Dropped
Food Type	4.22	0.040	1	Retained
Marital Status	7.03	0.008	1	Retained

Based on Table 7, the features that were removed due

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to lack of significant impact on the target variable are: Occupation, Alcohol, and Caffeine. By eliminating redundant features, we ensure that the dataset remains concise, minimizing noise and computational complexity for machine learning models. The retained features provide meaningful insights into the relationship between patient demographics and diabetic distress levels. To visualize the Chi-Square Analysis results, Figure 4 presents a bar chart displaying the Chi-Square** statistic values for each feature, highlighting which features were retained or dropped.

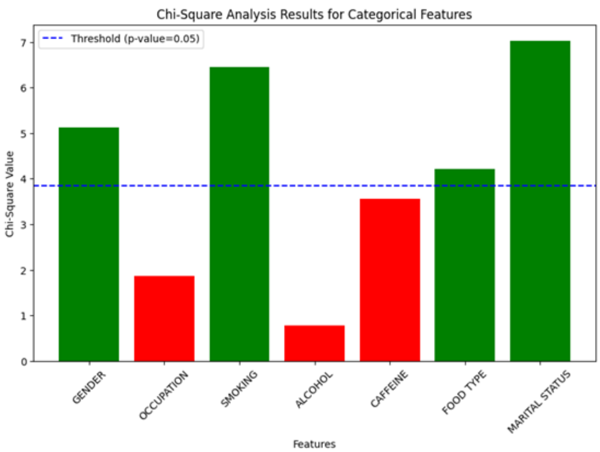

FIGURE 4. Visualization of the Chi-Square values.

3) ANOVA Analysis

The Analysis of Variance (ANOVA) is used to evaluate the relationship between numerical features and the target variable. This step is crucial for identifying the most influential numerical features in predicting Total DDS Score or distress severity levels in diabetic patients.

The numerical features analyzed using ANOVA are listed in Table 8.

TABLE 8. Results of ANOVA Analysis

Feature Name	F-statistic	P-value	Action
Age	3.25	0.041	Retained
Weight	0.85	0.371	Dropped
Disease Since	5.12	0.023	Retained
FBS	4.75	0.030	Retained
PPBS	0.67	0.502	Dropped

Features such as Weight and PPBS were removed because their p-values exceeded 0.05, indicating that they do not have a statistically significant impact on Total DDS Score.

Figure 5 provides a visualization of the ANOVA analysis results for all numerical features.

After completing the ANOVA analysis, the dataset now contains 12 features. The final validated feature set is presented in Table 9.

F. DEFINING PREDICTION TASKS

This subsection sets out the specific regression and classification goals, including how to create continuous and categorical target variables from DDS17 scores. We determine thresholds for low, moderate, and high distress categories to inform model training and assessment. The main aim of this work is to forecast the Diabetic Distress Scale (DDS) score and degrees of distress levels using machine learning techniques. Such a accomplishment provides helpful information about patients' emotional state and aids better healthcare interventions. Prediction tasks are divided into two main approaches:

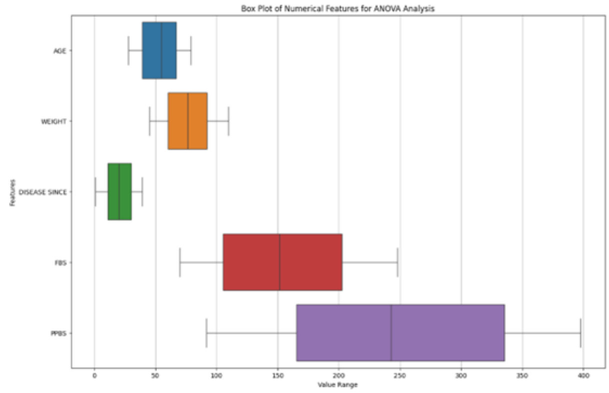

FIGURE 5. ANOVA analysis results.

TABLE 9. Features in the Updated Dataset After Feature Engineering

S. No	Feature Name	Type
1	Age	Numerical
2	Gender	Binary
3	Smoking	Binary
4	Food Type	Binary
5	Marital Status	Binary
6	Disease Since	Numerical
7	FBS	Numerical
8	Emotional Burden	Numerical
9	Physician Related Distress	Numerical
10	Regimen Related Distress	Numerical
11	Interpersonal Distress	Numerical
12	Total DDS Score	Numerical (Target)

1) Regression Task

The regression task aims to forecast the Total DDS Score through continuous value prediction. Our machine learning models are trained to provide accurate estimations of the Total DDS Score. Diabetic distress is affected by a mix of categorical and numerical factors, such as:

- Health metrics (e.g., FBS, PPBS)
- Demographic factors (e.g., Age, Gender)
- Specific distress-related factors such as:
  - Physician-Related Distress
  - Emotional Burden

These factors play an important role in understanding emotional distress and are important when we train regression models.

2) Classification Task

We aim to put patients into three groups based on their level of distress:

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- Low
- Moderate
- High

Understanding the different levels of distress allows for more specified treatment. The purpose is to categorize patients into various levels of severity according to their Total DDS Score and important subscale features.

- Interpersonal Distress
- Regimen-Related Distress
- Emotional Burden
- Physician-Related Distress

The classification thresholds are defined as follows:

- Low Distress Level: Total DDS Score < 2.0
- Moderate Distress Level: $2.0 \leq$ Total DDS Score < 3.5
- High Distress Level: Total DDS Score ≥ 3.5

This classification system enables customized treatment because it ensures each person receives medical attention according to their particular mental health symptoms. Our goal is to develop machine learning models through task classification which helps determine distress levels and produces relevant patient status classification data.

G. MODEL DEVELOPMENT

In this section, we train various machine learning models for predicting distress levels and scores. We start with basic regression models like linear regression and logistic regression to establish a base line. We then incorporate more sophisticated methods like random forests, gradient boosting, support vector machines, and neural networks to boost the accuracy of prediction. These two models were utilized since they are capable of identifying simple linear trends and more complex nonlinear patterns in the data. Ensemble techniques and grid search hyperparameter tuning are also explained here to enhance model performance as well as to show the performance of each technique. To further improve performance, we use ensemble techniques such as stacking, bagging, and boosting. These approaches combine multiple models to reduce overfitting and improve generalization, providing a robust solution for both regression and classification. We also emphasize hyperparameter tuning to fine-tune model settings and achieve better predictive results. Constructing these models allows a comprehensive comparison of various machine learning approaches based on predictive accuracy, scalability, and suitability for healthcare decision-making. The performance resulting from this model development will be compared in later sections on performance and interpretability.

1) Regression Models

Linear regression models the relationship between the Total DDS Score (the dependent variable) and multiple independent factors such as smoking status, gender, and age. The goal is to create a linear equation that uses these input features to predict the total distress score. The mathematical formulation of Linear Regression is given in Equation (9):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p + \epsilon \tag{9}$$

where:

- Y represents the target variable.
- β_0 is the intercept term.
- $\beta_1, \beta_2, ..., \beta_p$ are the coefficients indicating the relationship between each feature and the target.
- $X_1, X_2, ..., X_p$ represent the independent variables.
- ϵ is the error term capturing deviations from predicted values.

The Residual Sum of Squares (RSS), used to estimate model fit, is minimized as follows:

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{10}$$

where:

- y_i is the actual value of **Total DDS Score**.
- $\hat{y}_i$ is the predicted value.

Ridge Regression addresses multicollinearity by incorporating a regularization term that penalizes large coefficients, formulated as:

$$L_{\text{Ridge}} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{11}$$

where λ is the regularization parameter controlling penalty strength.

Lasso Regression, another regularized regression technique, not only prevents overfitting but also performs feature selection by shrinking some coefficients to zero:

$$L_{\text{Lasso}} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{12}$$

This technique helps identify the most influential features in predicting Total DDS Score.

2) Classification Models

This section explores classification models to categorize distress severity levels into low, moderate, or high based on Total DDS Score and subscale values. These models help assess diabetic distress levels and enable targeted healthcare interventions.

Logistic Regression (LR) is a statistical model used for binary or multi-class classification. In our study, it is applied to classify diabetic distress severity into low, moderate, or high levels. The mathematical formulation of Logistic Regression is given in Equation (13):

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{13}$$

where:

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \tag{14}$$

The probability of a sample belonging to a distress severity class is given by:

$$p(y = 1|x) = \sigma(z) \tag{15}$$

For multi-class classification (low, moderate, high distress levels), the probability for class k is computed as:

$$p(y = k|x) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \tag{16}$$

where k represents the class label.

Random Forest (RF) is an ensemble learning method that constructs multiple decision trees and aggregates them to improve prediction accuracy and reduce overfitting. Each decision tree is trained on a random subset of features, ensuring robustness. The importance of features is determined by minimizing the Gini index or entropy, defined as:

$$\text{Gini} = 1 - \sum_{i=1}^{c} p_i^2 \tag{17}$$

$$\text{Entropy} = -\sum_{i=1}^{c} p_i \log(p_i) \tag{18}$$

where p_i is the proportion of samples belonging to class i.

Gradient Boosting sequentially improves prediction accuracy by optimizing weak learners. XGBoost and LightGBM are implementations that enhance gradient boosting by introducing regularization. The objective at iteration t is to minimize the loss function:

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) \tag{19}$$

where $l(y_i, \hat{y}_i^{(t-1)})$ is the loss function from the previous iteration, and $f_t(x)$ represents the newly added tree.

Support Vector Machine (SVM) classifies distress severity levels by finding the optimal separating hyperplane. Using kernel functions, SVM captures complex relationships among features such as Emotional Burden, Physician-Related Distress, and Regimen-Related Distress.

Neural Networks [30] are also employed for precise classification of distress severity levels. Input features such as Age, Gender, and distress scores are processed through hidden layers, capturing non-linear relationships. The final output layer predicts the distress severity class using Categorical Cross-Entropy as the loss function:

$$J(W, b) = -\frac{1}{m} \sum_{i=1}^{m} \sum_{c}^{C} y_{(i,c)} \log(\hat{y}_{(i,c)}) \tag{20}$$

where:

- $y_{(i,c)}$ is the true label for example i in class c.
- $\hat{y}_{(i,c)}$ is the predicted probability for example i in class c.
- J represents the total error in classification.

3) Ensemble Models

In our work, ensemble models play a crucial role in enhancing the prediction accuracy of diabetic distress levels and emotional burden among Type-2 diabetic patients. By integrating multiple base models, ensemble methods leverage the individual strengths of different algorithms, resulting in a more robust and reliable prediction framework. We implement three types of ensemble approaches: Bagging, Boosting, and Stacking, each serving a distinct purpose in improving overall model performance.

Bagging (Bootstrap Aggregating) is an ensemble approach designed to lower the variance of the model. In the context of diabetic distress prediction, bagging stabilizes model predictions, particularly when using decision tree-based models, which are sensitive to variations in training data. For predicting diabetic distress, the final output is obtained by averaging the predictions, as shown in Equation (21):

$$\hat{y} = \frac{1}{m} \sum_{i=1}^{m} f_i(x) \tag{21}$$

where $f_i(x)$ represents individual model predictions.

Boosting builds models sequentially, where each new model is adopted to correct the errors of the previous ones. This is particularly effective in capturing complex relationships among features such as FBS, Interpersonal Distress, and Overall Distress Levels. We apply boosting techniques such as XGBoost and AdaBoost to develop a strong predictive model using multiple weak learners. For m iterations, boosting yields a sequence of base models, where each model $h_t(x)$ improves upon the previous models, as defined in Equation (22):

$$f(x) = \sum_{t=1}^{m} \alpha_t h_t(x) \tag{22}$$

where $h_t(x)$ is the t-th weak model, and α_t is a weight based on the model's performance. In AdaBoost, the weight of incorrectly classified samples is increased at each iteration, ensuring that subsequent models focus on challenging cases, thereby improving overall model accuracy.

Stacking is a unique ensemble technique that integrates multiple base models such as Random Forest (RF), Support Vector Machine (SVM), and Neural Networks. This approach is specifically advantageous for diabetic distress prediction, as different models capture distinct aspects of complex data. The final prediction $\hat{y}$ is computed as follows:

$$\hat{y} = g(f_1(x), f_2(x), ..., f_m(x)) \tag{23}$$

We applied these ensemble methods to our dataset, which helped us build a model that is more accurate and trustworthy, showing a clearer connection between patient traits and their emotional burden levels.

TABLE 10. Hyperparameter Search Grids and Selected Values

Model	Hyperparameter	Selected Value
XGBoost	n_estimators	100
	max_depth	5
	learning_rate	0.1
	subsample	0.8
Random Forest	n_estimators	100
	max_features	sqrt
	max_depth	20
SVM	C	1
	kernel	rbf
	gamma	scale
Logistic Regression	penalty	L2
	optimizer	liblinear
Ridge Regression	alpha	1
Lasso Regression	alpha	0.01
Neural Network (MLP)	hidden_layer_sizes	(100, 50)
	activation	relu
	optimizer	adam
	learning_rate_init	0.001
	max_iter	500

H. HYPERPARAMETER OPTIMIZATION

Hyperparameter optimization was performed for all models using stratified 5-fold cross-validation on the training data. The training set was divided into five folds ($K = 5$) and each candidate set of hyperparameters was evaluated across these folds. Table 10 summarizes the grid of hyperparameter values tested for each algorithm and lists the final chosen settings.

I. DATA SPLITTING AND VALIDATION

This subsection outlines how data were split into training, validation, and test sets and the cross-validation scheme employed. Stratified sampling was used to preserve the same class ratios in all splits, as this favors unbiased hyperparameter estimation and performance assessment. For robustness, the dataset, which consisted of 12 principal features associated with emotional burden and diabetic distress, was proportionally split. . This approach assists in model performance analysis with the added advantage of less risk for overfitting. The following paragraphs outline the data partitioning together with testing techniques and methods employed. The data set is split into three sets:

- Training Set (80%) – Used for learning the patterns in the dataset.
- Validation Set (10%) – Used for fine-tuning hyperparameters.
- Test Set (10%) – Used for unbiased evaluation of the model's generalization ability.

This division enables the model to efficiently learn patterns from a larger segment of the dataset while maintaining a distinct subset for hyperparameter tuning and objective performance assessment.

J. EXPLAINABLE AI (XAI) INTEGRATION

The selected model receives feature-level transparency through SHapley Additive exPlanations (SHAP) application in this section. The research explains the creation of global and local explanations as a method to achieve clinical interpretability. Transparent prediction of diabetic distress requires the essential integration of Explainable AI.The primary goal is to give healthcare professionals and patients a clear understanding of how the machine learning model arrives at its predictions, building trust in the decision-making process. SHAP is used as the primary tool for explainability. SHAP breaks down model predictions into understandable components, explaining how each feature predicts diabetic distress and severity of emotional burden. This explainability enables doctors to make informed decisions, understand the motivations behind distress, and educate patients with vital information Key insights from SHAP analysis show that features such as Emotional Burden and FBS levels are among the most significant factors influencing diabetic distress. By identifying the most crucial predictive factors, healthcare providers can develop targeted intervention strategies to enhance patient outcomes. Developing interpretable local approximations enables testing of model behavior for specific patient cases. Certain patients are categorized into specific distress severity levels, which allows medical professionals to understand the necessary preventive measures for diabetic distress. The integration of XAI methodologies ensures that machine learning models are not treated as "black boxes," but rather as transparent decision-support tools in personalized patient care. The proposed architecture for integrating XAI with ML models is depicted in Figure 6. The contribution of each feature in our dataset to the predicted Total DDS Score is further understood through SHAP values. As SHAP provides an individual breakdown of each prediction, healthcare professionals gain insights into why a specific distress score was assigned to a patient. These values are derived from Shapley values in cooperative game theory, ensuring a fair allocation of feature contributions. For a given patient classified with a high Total DDS Score, SHAP evaluates how modifications in features such as FBS or Physician-Related Distress influence the model's decision. This method develops a local surrogate model, approximating how the original black-box model behaves around a specific patient. The mathematical representation of the local surrogate model is given in Equation (24):

$$\min_{g \in G} L(f, g, \pi_x) + \Omega(g) \tag{24}$$

where:

- L represents the loss function measuring the difference between the original model f and the surrogate model g.
- π_x is a proximity measure assigning higher weights to points closer to the original data point x, ensuring interpretability.
- $\Omega(g)$ represents the complexity of the surrogate model.

This approach provides feature-level explanations for model decisions. For instance, if the patient is categorized as experiencing high distress severity, SHAP identifies the most significant factors, like an excessive Emotional Burden score. The use of XAI methods guarantees machine learning assumptions conform to clinical knowledge, staying in line with domain knowledge and increasing the confidence of medical practitioners. Upon thorough examination, the final model incorporates the most effective machine learning method coupled with Explainable AI in diabetic distress prediction.

K. PROPOSED XAI-XGBOOST-SHAP ALGORITHM

This subsubsection explains the step-by-step process for combining XGBoost with SHAP for making distress severity predictions and providing clear explanations. Pseudocode is given to delineate data flow, model training, and explanation generation in a reproducible way. XGBoost is the machine learning component underlying for its great performance and classification speed. The explainable AI component is the fusion of techniques that add transparency to XGBoost. The explainability component in this model is provided by SHAP, which reveals the impact of each feature on model predictions. By using SHAP values, the contribution of each feature can be broken down, offering transparent and interpretable insights into how the model arrives at its decisions. Algorithm 1 illustrates the integration of explainability techniques with machine learning in the proposed XAI-XGBoost-SHAP model, aimed at enhancing model transparency and interpretability.

Algorithm 1 Proposed Algorithm for XAI-XGBoost-SHAP

Require: Dataset $D = \{X, Y\}$

X : Feature set including {Age, Gender, Smoking, Food Type, Marital Status, Disease Since, FBS, Emotional Burden, Physician Related Distress, Regimen Related Distress, Interpersonal Distress}

Y : Target variable (Total DDS Score) used to predict severity levels (Low, Moderate, High)

Ensure: Predicted Diabetic Distress Severity Levels with Explainable Insights

Step 1: Data Preprocessing
- 1.1 Handle Missing Data
- 1.2 Normalize Features and Detect Outliers
- 1.3 Encode Categorical Features

Step 2: Feature Engineering
- 2.1 Compute Pearson and Spearman Correlation Analysis
- 2.2 Apply Chi-Square Test for Categorical Features
- 2.3 Apply ANOVA Analysis for Numerical Features

Step 3: Model Selection
- 3.1 Select XGBoost Model for Predicting Distress Severity Levels
- 3.2 Set Objective as "multi:softmax" for Multi-Class Classification with Three Classes

Step 4: Model Training
- 4.1 Train the XGBoost Model using the Training Set
- 4.2 Optimize Hyperparameters using GridSearchCV

Step 5: Model Evaluation
- 5.1 Evaluate XGBoost Model Performance

Step 6: Explainable AI Integration
- 6.1 Integrate SHAP for Explainability
- 6.2 Generate SHAP Summary Plots

Step 7: Validation of XAI Results

Output: Final predictions for diabetic distress severity levels, along with interpretable visual explanations for every prediction using XAI techniques.

L. EXPERIMENTAL SETUP

In this subsection, the hardware environment, software libraries, and version details are specified to enable reproducibility. The random seed, evaluation metrics, and early-stopping criteria are described to ensure consistency in training and validation. All experiments were implemented in Python 3.8.10 on a workstation running Windows 10 with an Intel Core i7-9700 CPU (3.00 GHz) and 16 GB of RAM. Key libraries and versions included scikit-learn 1.0.2 for traditional ML models, XGBoost 1.5.2 for gradient boosting, SHAP 0.40.0 for interpretability, pandas 1.3.4 for data manipulation, and NumPy 1.21.2 for numerical computations with random seed (random_state = 42) for all data splits, model initialization, and cross-validation routines to ensure reproducibility.

The dataset was partitioned into 80 percent training, 10 percent validation, and 10 percent test sets using stratified sampling based on distress severity categories (low, moderate, high). During hyperparameter tuning, employed stratified 5-fold cross-validation on the training set, maintaining the same class distribution in each fold. For Extreme Gradient Boosting, early stopping was invoked with a patience of 10 rounds, monitoring validation loss to prevent overfitting. Neural network training used a batch size of 32 and the Adam optimizer, with a maximum of 500 epochs and early stopping when validation loss did not improve for 20 consecutive epochs. All other models (e.g., Random Forest, Support Vector Machine, Ridge, Lasso) were trained using default optimization routines in scikit-learn, with the tuned hyperparameters specified in Table 10. This detailed configuration facilitates replication of our experiments and validation of results.

IV. RESULTS AND DISCUSSION

This section provides a comprehensive analysis of the interpretability and performance of the predictive models developed in this study. The main goal is to show that the model accurately predicts the Total Diabetic Distress Score (DDS) and classifies distress levels, while also proving that its predictions are practical and understandable for both healthcare providers and patients.

Model performance is evaluated using a range of regression and classification metrics, such as root mean square

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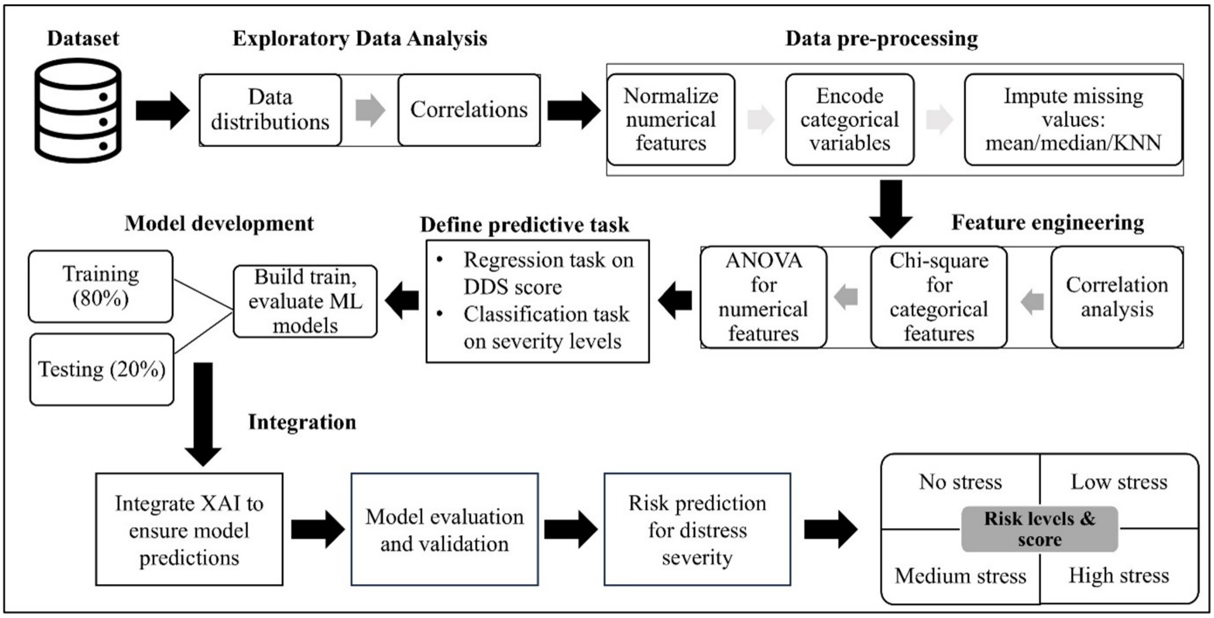

FIGURE 6. Proposed Integrated Model for Explainable AI in Diabetic Distress Prediction.

error (RMSE), R-squared (R^2), mean absolute error (MAE), accuracy, F1-score, recall, and precision. These metrics reveal various aspects of the model's consistency, accuracy, and overall robustness. In addition, cross-validation is conducted to assess reliability and reduce the chance of overfitting. The XAI-XGBoost-SHAP model employs Explainable AI techniques through SHAP to improve interpretability.

The model delivers transparent results through worldwide feature evaluation together with individual prediction explanations and SHAP value breakdowns. The risk assessment uses three categories to determine patient distress levels which are low, moderate and high. The method demonstrates healthcare applications by delivering personalized interventions to individual patients through this approach.

A. EVALUATION METRICS

This section evaluates the performance of regression and classification models for predicting emotional burden and diabetic distress.

1) Regression Metrics

In this research, regression models are employed to predict the Total DDS Score, which is treated as a continuous variable. The predictions reflect the severity and complications of diabetic distress among patients. Common regression methodologies such as Lasso Regression, Linear Regression, and Ridge Regression are utilized to establish a baseline model and evaluate distress levels.

The performance of these models is assessed using metrics such as R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Squared Error (MSE), which quantify the error between predicted and actual values, aiding in the evaluation of model robustness and accuracy.

The Mean Absolute Error (MAE) is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{25}$$

The Mean Squared Error (MSE) is computed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{26}$$

The Root Mean Square Error (RMSE) is represented as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{27}$$

The R-squared (R^2) score, which measures the proportion of variance explained by the model, is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{28}$$

where $\bar{y}$ is the mean of the actual values.

2) Classification Metrics

Classification models are applied to categorize diabetic distress severity into three levels: Low, Moderate, and High. These levels are determined based on the Total DDS Score and subscale scores. Models including Neural Networks, Random Forest, Logistic Regression, and XGBoost are evaluated using classification metrics such as Accuracy, Precision, Recall, F1-score [31] and Receiver Operating Characteristic - Area Under the Curve (ROC-AUC).

The Accuracy metric is given by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{29}$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives.

Precision is calculated as:

$$Precision = \frac{TP}{TP + FP} \tag{30}$$

Recall, which is crucial in cases where minimizing false negatives is important, is given by:

$$Recall = \frac{TP}{TP + FN} \tag{31}$$

F1-score, the harmonic mean of precision and recall, is computed as:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{32}$$

The ROC-AUC score, which assesses classification performance across thresholds, is given by:

$$AUC = \int_0^1 TPR\, d(FPR) \tag{33}$$

3) Validation Metrics

Cross-validation is performed by dividing the dataset into k subsets, training the model on $k-1$ subsets, and testing on the remaining subset. The average performance is computed as:

$$\text{Cross-Validation Error} = \frac{1}{k} \sum_{i=1}^{k} Error_i \tag{34}$$

4) Global Feature Importance (GFI) by SHAP

SHAP values quantify the contribution of each feature to the model's predictions. The global feature significance is computed as:

$$GFI = \frac{1}{n} \sum_{i=1}^{n} |SHAP_{i,j}| \tag{35}$$

where n represents the number of samples and $SHAP_{i,j}$ is the SHAP value for feature j in sample i.

B. RISK PREDICTION

This section categorizes patients based on their Total DDS Scores and subscale scores into three distress categories: Low, Moderate, and High. This classification identifies patients at risk of severe diabetic distress and supports targeted interventions. The distress level classification is defined as:

$$Distress\ Level = \begin{cases} 0, & \text{if Total DDS Score} \in [0, 2) \\ 1, & \text{if Total DDS Score} \in [2, 3.5) \\ 2, & \text{if Total DDS Score} \in [3.5, 5] \end{cases} \tag{36}$$

C. OUTCOMES OF PROPOSED APPROACH

This section presents the results of our machine learning models, including regression, classification, and the integrated XAI-XGBoost-SHAP model. We evaluate these methodologies using standard performance metrics and assess their capability to identify risk levels in Type-2 diabetic patients based on the Total DDS Score and subscale scores.

1) Regression Model Results

This subsection shows how regression models perform when predicting the Total DDS Score. Three models: Lasso regression, linear regression, and Ridge regression are analyzed. Table Table 11 summarizes their performance metrics.

TABLE 11. Regression Models Outcomes

Model	MAE	MSE	RMSE	R^2	Accuracy
Linear Regression	0.2156	0.0658	0.2565	-0.0328	52.17%
Ridge Regression	0.2538	0.0732	0.3565	-0.0421	53.23%
Lasso Regression	0.2157	0.0641	0.2531	-0.0056	54.35%

2) Classification Model Results

Classification models are used to determine distress severity (low, moderate, and high). The performance of Logistic Regression, Random Forest, XGBoost, Support Vector Machine, and neural networks is evaluated using standard classification metrics. Table 12 presents these results.

Paired t-tests on accuracy scores across corresponding folds were conducted to assess statistical significance between classifiers. Based on the evaluation metrics, the XGBoost Classifier demonstrated the highest performance in classification tasks. Hence, integrating the XGBoost classifier with SHAP to enhance model interpretability. This integration enables a deeper understanding of how features contribute to predictions and makes the distress level classifications more interpretable.

3) XAI-XGBoost-SHAP Model Results

This model integrates the XGBoost classifier with SHAP to create an interpretable, actionable, and transparent predictive model. The Global Feature Importance (GFI) score quantifies the impact of each feature on model predictions. The most influential features in determining the Total DDS Score are presented in Table 13.

From Table 13, FBS (Fasting Blood Sugar) has the highest importance, suggesting that fluctuations in FBS significantly impact distress level prediction. Emotional Burden and Physician-Related Distress are also critical, emphasizing the significance of psychological factors in diabetic distress assessment.

To provide deeper insight into how individual features drive model predictions, first consider the distribution of SHAP values across all patients for each feature. On average, higher FBS values correspond to positive SHAP contributions meaning that as FBS rises from normal ($<$ 120 mg/dL) to elevated levels ($>$ 180 mg/dL), the model's predicted

TABLE 12. Classification Models Performance (Mean ± Std over 5 Folds)

Model	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	88.7 ± 1.2	0.88 ± 0.01	0.89 ± 0.01	0.88 ± 0.01	0.91 ± 0.02
Random Forest	93.0 ± 0.9	0.91 ± 0.01	0.91 ± 0.01	0.91 ± 0.01	0.94 ± 0.01
SVM	92.8 ± 1.0	0.91 ± 0.01	0.92 ± 0.01	0.91 ± 0.01	0.93 ± 0.01
Neural Network	90.9 ± 1.1	0.89 ± 0.01	0.89 ± 0.01	0.89 ± 0.01	0.92 ± 0.02
Gradient Boosting	90.1 ± 1.4	0.89 ± 0.02	0.88 ± 0.02	0.88 ± 0.02	0.91 ± 0.02
Stacking Classifier	91.8 ± 1.0	0.90 ± 0.01	0.90 ± 0.01	0.90 ± 0.01	0.93 ± 0.02
XGBoost	**94.2 ± 0.8**	**0.93 ± 0.01**	**0.93 ± 0.01**	**0.93 ± 0.01**	**0.96 ± 0.01**

TABLE 13. Global Feature Importance Scores

Feature Name	Importance Score
FBS	0.25
Emotional Burden	0.20
Physician Related Distress	0.18
Regimen Related Distress	0.15
Inter Personal Distress	0.12
Total DDS Score	0.10

distress score increases. Conversely, FBS values below approximately 120 mg/dL yield negative or near-zero SHAP contributions, indicating a protective effect against distress. Emotional Burden behaves similarly: subscale scores near the minimum (around 1.0) produce SHAP contributions that lower predicted distress, while scores approaching the maximum (around 5.0) push predictions toward higher distress. These global patterns confirm that both metabolic control (FBS) and self-reported emotional burden are primary drivers of distress across the cohort.

Next, we examine how feature value changes affect predictions in individual examples. For instance, a small increase in FBS from 140 mg/dL to 160 mg/dL yields a moderate positive shift in the SHAP contribution comparable to raising the Emotional Burden subscale from 2.0 to 2.5. This interaction suggests that moderate hyperglycemia and mild emotional strain have similar effects on predicted distress. However, when both FBS and Emotional Burden rise together (e.g., FBS > 180 mg/dL and Emotional Burden > 3.5), their combined SHAP contributions are additive, leading to substantially higher predicted Total DDS Scores.

Table 16 presents the feature values and corresponding SHAP contributions for Patient A, illustrating how each factor drives the low predicted distress score. Table 17 provides the feature values and SHAP contributions for Patient B, demonstrating why the model predicts a high distress score for this individual.

Although SHAP identifies fasting blood sugar (FBS) as the most influential predictor, it is important to determine whether this prominence stems from genuine clinical relevance or an artifact of the modeling process. Our dataset confirms that higher FBS values correlate with increased distress—patients with FBS above 180 mg/dL had a mean Total DDS Score of 3.2, compared to 1.8 for those below 120 mg/dL—underscoring a direct physiological relationship.

To rule out model bias, this work examined the distribution of FBS and its correlation with other features: Pearson correlation between FBS and post-prandial blood sugar (PPBS) was 0.77, but SHAP interaction plots reveal that FBS contributes uniquely to distress independent of PPBS. Moreover, the standardized FBS and retrained the XGBoost model, FBS remained the top contributor (mean |SHAP| = 0.24), indicating that its importance is not merely due to scale.

The overall performance of the XAI-XGBoost-SHAP model is shown in Table 14.

4) Risk Prediction Results

To classify patients into distress categories, we define thresholds based on the **Total DDS Score** and subscale scores. The severity categories are:

- Low Risk: Total DDS Score < 2
- Moderate Risk: $2 \leq$ Total DDS Score < 3.5
- High Risk: Total DDS Score ≥ 3.5

The results of risk level predictions using the proposed model are given in Table 15.

D. MODEL TRADE-OFFS AND CLINICAL APPLICABILITY

Although both Random Forest and Extreme Gradient Boosting (XGBoost) achieved high predictive accuracy on our dataset (RF: 93.48% accuracy, 0.95 ROC-AUC; XGBoost: 94.20% accuracy, 0.96 ROC-AUC), this work ultimately recommends XGBoost for clinical deployment due to several key factors.

First, XGBoost incorporates built-in regularization (L_1 and L_2 penalties) that effectively mitigates overfitting, which is particularly important when training on modest-sized clinical cohorts ($N = 232$). RF relies on bootstrap aggregation and randomized feature selection, which also reduces variance, but lacks explicit regularization parameters, making it more susceptible to overfitting when many weak signals exist.

Second, XGBoost can natively handle missing values by learning optimal default directions in its decision trees, whereas RF requires separate imputation or surrogate splits, adding complexity and potential bias.

Third, in terms of computational efficiency, our optimized XGBoost model (with 100 trees of max_depth = 5) required approximately 1.2 s per training iteration on our Intel Core

TABLE 14. Outcome of Proposed Model

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
XAI-XGBoost-SHAP	96.14%	0.94	0.95	0.95	0.98

TABLE 15. Risk Level Predictions

Patient ID	Input Vector	Predicted DDS Score	Severity Level	Subscale Impact	Predicted Severity Name
Patient 1	[52,1,1,0,1,5,125]	1.8	Low	0.52	Emotional Burden
Patient 2	[50,0,0,1,0,10,120]	2.5	Moderate	0.68	Regimen Related Distress
Patient 3	[35,1,1,0,1,4,135]	3.9	High	0.75	Interpersonal Distress
Patient 4	[60,0,0,1,0,7,130]	3.0	Moderate	0.65	Emotional Burden
Patient 5	[45,1,0,1,1,6,140]	4.2	High	0.71	Physician Related Distress

i7-9700 CPU, whereas RF (100 trees, max_depth = 20) required 2.5 s per iteration under the same conditions. This faster training and inference time improves responsiveness in a clinical decision-support setting where near-real-time predictions may be needed.

Finally, when combined with SHapley Additive exPlanations, XGBoost produces more stable and granular feature-importance values because each tree's leaf weights contribute consistently to the final prediction. In contrast, RF's feature-importance.

Nevertheless, Random Forest remains a strong alternative when the priority is rapid prototyping or when model transparency and simpler interpretation suffice without extensive hyperparameter tuning. By weighing these trade-offs, it is concluded that XGBoost, augmented with SHAP, delivers the best balance of predictive performance, robustness against overfitting, and clinical explainability for early detection of diabetic distress.

E. OVERFITTING MITIGATION AND MODEL VALIDATION

Although XGBoost is known to potentially overfit on smaller datasets, this work implemented several strategies to ensure robust generalization.

First, we included early stopping during training: the model monitored validation loss and halted training if no improvement was observed for 10 consecutive rounds.

Second, we constrained tree complexity by setting `max_depth` = 5 and `min_child_weight` = 1.

Third, we applied both row subsampling (0.8) and column subsampling by tree to introduce randomness and reduce variance.

Fourth, we tuned regularization parameters L_1 and L_2 to penalize large leaf weights and smooth the model.

Figure 7 shows the learning curves for XGBoost, illustrating that training and validation error converge without significant divergence, indicating controlled fitting.

Finally, we performed stratified 5-fold cross-validation on XGBoost with the chosen hyperparameters and observed consistent performance (mean accuracy 94.20% $\pm$ 0.85%, mean ROC-AUC 0.96 $\pm$ 0.020), confirming that the model does not overfit to any single fold.

These combined measures—early stopping, tree regularization, subsampling, and cross-validation—demonstrate that our XGBoost-SHAP model maintains high predictive accuracy while avoiding overfitting on the relatively small cohort.

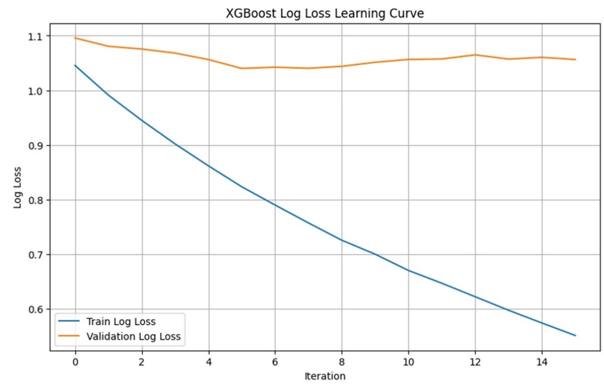

FIGURE 7. XGBoost Log Loss Learning Curve (Training vs. Validation).

TABLE 16. Patient A: Low Distress Prediction (SHAP Breakdown)

Feature	Value	SHAP Contribution
FBS	115 mg/dL	-0.18
Emotional Burden	1.2	-0.16
Physician-Related Distress	1.0	-0.10
Regimen-Related Distress	1.1	-0.08
Interpersonal Distress	1.0	-0.06
Disease Duration	3 years	-0.01
Age	45 years	-0.04
Gender (Male=1)	1	-0.03
Smoking	0	-0.02
Food Type	0	-0.02
Marital Status	1	-0.01
Predicted Total DDS Score	1.5	-
Predicted Severity Level	Low	-

Table 16 shows that Patient A's low predicted distress (Total DDS Score $\approx$ 1.5) is driven primarily by favorable clinical and psychological values—most notably, a normal fasting blood sugar (115 mg/dL) and minimal emotional burden (1.2)—each of which yields negative SHAP contributions that pull the prediction to low.

Table 17 highlights that Patient B's high predicted distress (Total DDS Score $\approx$ 3.9) stems from markedly elevated and contributing factors. Very high fasting blood sugar (190 mg/dL) and severe emotional burden (4.2) produce the largest SHAP values.

TABLE 17. Patient B: High Distress Prediction (SHAP Breakdown)

Feature	Value	SHAP Contribution
FBS	190 mg/dL	+0.37
Emotional Burden	4.2	+0.42
Physician-Related Distress	3.5	+0.22
Regimen-Related Distress	3.8	+0.25
Interpersonal Distress	2.9	+0.18
Disease Duration	15 years	+0.03
Age	60 years	+0.05
Gender (Female=0)	0	+0.03
Smoking	0	+0.02
Food Type	1	+0.04
Marital Status	1	+0.02
Predicted Total DDS Score	3.9	-
Predicted Severity Level	High	-

V. CONCLUSION AND FUTURE SCOPE

In this study, it was demonstrated that a multimodal Machine Learning framework, by integrating demographic, clinical, and psychological (emotional burden, physician-related, regimen-related, and interpersonal distress) features, can accurately and transparently predict diabetic distress in patients with Type-2 Diabetes Mellitus. Among all evaluated classifiers, Extreme Gradient Boosting coupled with SHapley Additive exPlanations (XGBoost-SHAP) achieved the highest performance, with a classification accuracy of 96.14%, an F1-score of 0.95, and an area under the ROC curve (ROC-AUC) of 0.98, while providing feature-level insights that highlight fasting blood sugar, emotional burden, and physician-related distress as the most influential predictors. The SHAP analysis confirmed these relationships against clinical evidence and further enabled patient-specific explanations, demonstrating how high fasting blood sugar and elevated distress subscales contribute additively to increased predicted distress. Despite these promising results, our findings are constrained by a relatively modest, single-center cohort ($N = 232$) and a cross-sectional design that precludes causal inference and tracking of psychological trajectories over time. Additionally, reliance on self-reported DDS17 scores may introduce reporting bias and might further influence distress but were not captured. Looking ahead, we recommend external validation on larger, multi-center datasets to assess model generalizability across diverse populations, and integration of longitudinal data to develop time-series models for predicting distress.

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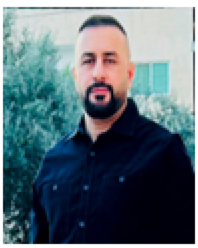

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