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Enhancing Migraine Diagnosis and Classification with TabNet: A Data-Driven Approach

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***Abstract*—In recent years, significant advancements in healthcare analytics have shown immense potential in enhancing patient care and clinical decision-making. This research delves into innovative methods for precise migraine classification using TabNet, a state-of-the-art deep learning model specifically designed for tabular data. Migraine, a debilitating neurological condition, poses challenges in accurate categorization and effective management. Our method utilizes the capabilities of TabNet to establish a robust system for classifying various migraine subtypes. We leverage a rich array of clinical and patient-reported data to enable accurate, automated diagnosis. This research underscores the impact of advanced analytical techniques in healthcare, offering a more personalized, data-centric approach to diagnosing and treating migraines. Our findings reveal an impressive 98% accuracy in overall migraine classification, outperforming other methods, and an exceptional approximate 99% accuracy in identifying specific migraine subtypes. Through TabNet, we aim to advance healthcare analytics, providing healthcare professionals with enhanced tools for patient care and contributing to the broader field of precision medicine.**

***Index Terms*—Migraine, TabNet, Precision Medicine, Deep Learning, Data-driven Diagnosis.**

I. Introduction

Migraine is a multifaceted neurological disorder characterized by recurrent, disabling headaches, often accompanied by a variety of symptoms such as nausea, vomiting, and increased sensitivity to light and sound. With approximately 1 billion people worldwide affected by the condition, it is the third most prevalent medical condition globally [1]. The extensive personal and societal burden of migraines includes reduced quality of life and significant economic costs resulting from health care utilization and lost productivity. Accurate classification of migraine types and prediction of effective drugs are paramount to managing this condition and improving the well-being of sufferers.

Traditionally, the diagnosis of migraine has relied on clinical assessment and patient-reported symptoms, which can be subjective and lead to misclassification. In addition, finding the most appropriate medication for migraine sufferers can be a challenging process of trial and error, given the wide variability in treatment effectiveness between individuals. Here is an application of machine learning. TabNet, a neural network designed for tabular data [2], is suitable for analyzing structured clinical data and classifying different types of migraine.

This research explores the ability of TabNet technology for classifying migraine varieties in the domain of migraine diagnosis. We intend to assess whether these advanced deep learning techniques can enhance the classification of various migraine types as well as suggest accurate personalized medication methods according to the International Classification of Headache Disorders standards [3]. Combining clinical data, patient histories, and treatment outcomes, this work seeks to expand our comprehension of migraine pathophysiology, ultimately allowing healthcare personnel to offer personalized treatments according to the requirements of every patient [4], for instance, migraine with/without aura, hemiplegic migraine, and chronic migraine.

TabNet is a powerful deep learning technique that can learn from tabular data, such as clinical records or demographic features. It can perform feature selection and interpretability, as well as achieve high accuracy and efficiency. By applying TabNet to migraine type classification, we aim to enhance migraine diagnosis and classification. We also compare TabNet with other models and demonstrate its superior performance. Our paper contributes to the growing body of knowledge that leverages artificial intelligence and graph-based techniques to improve the lives of migraine sufferers. Ultimately, our goal is to reduce the burden of this condition, minimize misclassifications, and optimize treatment outcomes for individuals living with migraines.

II. Related works

Recent advancements in automated systems for migraine classification and analysis have seen a surge in interest, particularly in the realm of computational techniques and machine learning methods. This section offers an overview of several notable studies in this domain. A significant study in this field utilized artificial neural networks for the automated classification of migraine cases, highlighting the prowess of machine learning in distinguishing between various migraine types [5]. This represents a considerable advancement towards more precise diagnosis and management of migraines. Another study introduced a novel approach using fuzzy logic and intelligent systems for migraine detection and analysis

[6]. Despite being a preprint and pending peer review, it suggests a promising, more interpretable, and flexible method for diagnosing migraines.

The use of electroencephalography (EEG) data combined with K-means clustering was explored in a different study for migraine detection [7]. The application of clustering techniques to EEG data, which provides insight into brain activity during migraine episodes, indicates a strong potential for pattern recognition in migraine diagnosis. A study that classified migraine patients using resting-state functional magnetic resonance imaging (fMRI) examined both static and dynamic functional connectivity patterns [8]. By using neuroimaging data, this method might greatly increase the accuracy of migraine categorization. An further significant research analyzed the distinctions between migraines in adults and children [9], providing information on the various strategies needed to treat these two different populations. Another example highlights the potential of machine learning for automated migraine diagnosis: supervised machine learning methods were used to categorize migraine patients [10]. This study provides the groundwork for more research in this field.

In a different research, deep learning methods were used to identify headache types and identify biomarkers from structural MRI images [11]. This study creates a new path for the accurate and automated identification of different types of headache diseases. In a research, migraine with aura was detected and classified using machine learning algorithms in combination with morphometric MRI data [12]. This illustrates how sophisticated imaging methods may improve migraine diagnosis and subtype categorization. An original research centered on the automated classification of self-reported narratives by individuals suffering from cluster headaches or migraines [13]. This demonstrates how patient narrative analysis may help with headache problem categorization. Another important strategy was to automate the categorization of headache diseases by combining machine learning with patient-reported questionnaires [14]. This aids in rapid and accurate diagnosis based on patient-reported symptoms. Beyond migraines, the development of a drug recommendation system in medical emergencies illustrates the wider applicability of AI-driven solutions in various medical conditions [15], including migraine treatment strategies.

The potential application of IoT and wearable sensors for stress detection in healthcare was explored in another study [16], indicating their possible use in monitoring and managing migraine conditions. Sentiment analysis in drug recommendation systems [17] reveals how machine learning can utilize patient reviews for suggesting suitable medications, which could be beneficial in migraine treatment. The potential for adapting collaborative filtering and clustering approaches from drug recommendation systems for diabetes patients, as discussed in [18], suggests their applicability in personalizing medication recommendations for migraine treatment. A comprehensive review of over-the-counter treatment options for chronic migraine headaches [19] provides a broad perspective on the current landscape of migraine management. The survey for the significance of automating the categorization of headache disorders, especially through the use of patient-reported questionnaires, as highlighted in reference [20]. The deep learning for drug recommendation and detecting adverse drug reactions (ADRs) for incorporating information from social media data, underscores the potential advantages of integrating varied data sources into healthcare decision support systems [21]. Collectively, these studies demonstrate a wide array of computational and machine learning approaches being applied to improve the classification, diagnosis, and treatment of migraine, heralding new, more accurate, and personalized healthcare solutions.

III. Methodology

A. Data Curation

In this research, we utilized the 'Migraine Classification Data Set, a valuable resource from a 2020 publication on the Migraine Classification Model [22]. The dataset comprises 400 medical records documenting individuals diagnosed with various migraine-related conditions. These records were meticulously gathered by trained medical personnel at the Centro Materno Infantil de Soledad during the initial quarter of 2013.

The dataset comprises 24 characteristics that are of the greatest significance in our study. It covers the diagnosis of seven different forms of migraine like 'Familial Hemiplegic Migraine,' 'Sporadic Hemiplegic Migraine,' 'Typical Aura with Migraine,' 'Migraine without Aura,' and also includes the classification of each type. These characteristics offer valuable insights into patient profiles and symptom patterns, providing crucial information for our study on migraine categorization. Noteworthy features include symptoms like Nausea, frequency of migraines, intensity of headaches, and the location of headaches, among others.

B. Data Preprocessing

To improve the quality of the migraine classification data, we successfully removed extraneous features from the dataset by employing decision trees. Subsequent to the implementation of this methodology, the accuracy of the classification of various types of migraines was considerably improved, and the chosen criteria were rendered pertinent. Our investigation endeavored to enhance the efficacy of the classification procedure by employing a logical data reduction methodology.

Fig. 1 presents a comprehensive overview of the sequential process employed in our research, showcasing the seamless flow of data through each step. Commencing with the initial data, we employ decision trees for feature selection, extracting essential characteristics. The refined data then progresses through the TabNet encoder, followed by the attentive TabNet decoder, effectively capturing essential characteristics and producing a weighted latent space representation. This exhaustive methodology ensures a meticulous and efficient process for migraine classification.

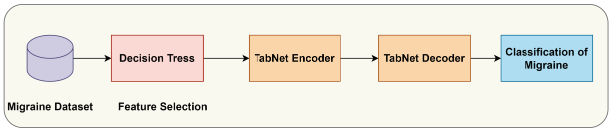

Fig. 1. Schematic Representation of our Migraine Classification Process

C. *TabNet Architecture*

TabNet is an interpretable deep learning architecture designed exclusively for tabular data, which is distinguished by a sequential attention mechanism that identifies crucial characteristics for decision-making. As shown in Fig. 2, the feature transformer, attentive transformer, and feature masking components work together in an iterative manner to process the TabNet encoder. In each iteration, the attentive transformer learns a mask that highlights important input qualities for the current choice. When choosing pertinent input characteristics for further iterations, the feature masking component is guided by this mask. For the final output, the TabNet encoder produces a latent space representation of the input data that is weighted by feature significance masks. The TabNet decoder then uses this representation.

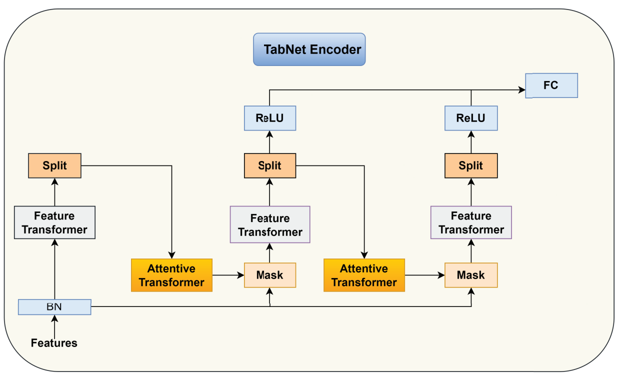

Fig. 2. TabNet Encoder Components

The feature transformer is a key component in normalizing and transforming input data into a better latent space representation that is tailored for TabNet. The attentive transformer, however, uses sequential attention to identify crucial characteristics at every decision point and even captures long-range correlations between input features. The feature masking component determines the important features for each choice based on the mask of the attentive transformer, improving TabNet's interpretability by exposing influential features.

A sequential neural network with a fully connected (FC) layer, a batch normalization (BN) layer, and a gated linear unit (GLU) activation function makes up the feature Transformer shown in Fig. 3. The GLU activation function enables the network to discover non-linear correlations between the input features. The FC layer transforms the input data into a new latent space representation. The BN layer normalizes the FC layer's output. The TabNet decoder uses feature blocks to learn a weighted latent space representation of the input data based on feature significance masks. The final result is then produced using this representation.

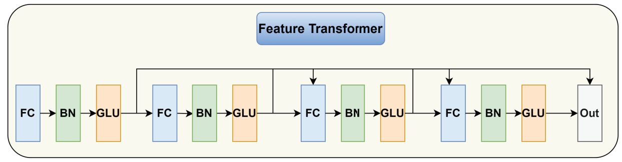

Fig. 3. Feature Transformer

Fig. 4 illustrates the special feature selection capabilities of the TabNet architecture's attentive transformer block. A single layer that combines previous scale information is included in this block, reflecting the historical significance of each element in the decision-making process. It is essential that previous use be included in the model since it enables the model to evaluate the contextual significance of characteristics. The model uses a sparsemax normalization approach to efficiently aggregate each feature's significance. Sparsemax is intended to provide a sparse output, in contrast to the conventional softmax function, allowing the model to preferentially concentrate on the most notable characteristics. By focusing on the most important data points, this deliberate emphasis on relevant attributes greatly improves the model's accuracy and efficiency in generating decisions.

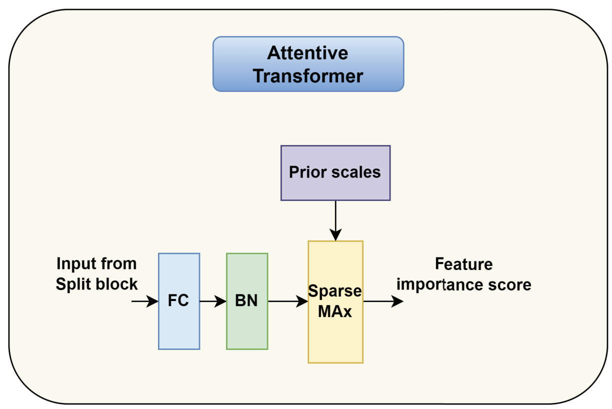

Fig. 4. Attentive Transformer

The TabNet decoder, a critical component that uses the selected and converted characteristics from the encoder to create predictions, is seen in Fig. 5. It makes use of a multi-phase decision-tree framework-related decision-making process. Adaptively choosing relevant characteristics and integrating them, it utilizes regression or classification to produce predictions at each level. Notably, by highlighting the significance of every feature in the decision-making process and so bringing transparency to the model's logic, the decoder provides a unique interpretability feature. Because TabNet must manage tabular data well, it is a good choice for a variety of data-driven tasks in a number of academic fields.

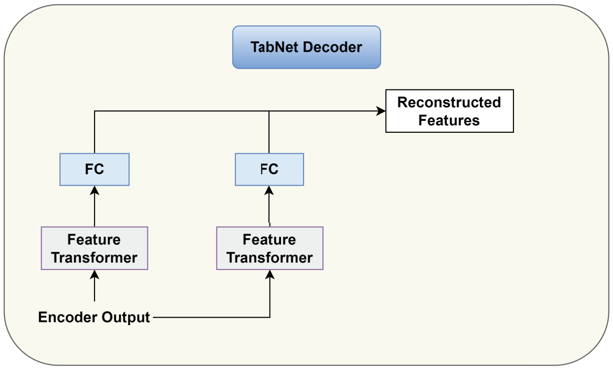

Fig. 5. TabNet Decoder Components

IV. Results and Discussion

A. Model Training

Table I provides an overview of the configuration parameters used to train the TabNet model—which was created specifically for the categorization of migraines. To prove the model's effectiveness and show its operation, several components are required.

TABLE I
TabNetClassifier Parameters

Parameter	Value
The dimensionality of the prediction layer.	64
The dimensionality of the attention mechanism.	64
The number of decision steps in the network.	10
gamma	0.5
The number of independently decision steps in each feature block.	6
The number of shared decision steps in each feature block.	6
epsilon	1×10^{-15}
The random seed for reproducibility.	0
verbose	1

B. Performance measures

A comprehensive study was carried out utilizing a variety of crucial performance measures to establish how successfully our system categorized distinct forms of migraines. All of these indicators were quite useful in determining the model's accuracy and reliability. Three essential metrics—Accuracy, Precision, and F1-Score—were used to measure the model's performance.

Accuracy: A calculation was made to determine what percentage of all forecasts produced were correct. The proportion of migraine instances that our model correctly identified was given, along with an evaluation of the algorithm's overall prediction accuracy.

Precision: A comparison was made between the total number of accurately predicted positive cases and the prediction accuracy of the model. Within the limitations of our migraine classification model, it assessed the extent to which individuals with real positive migraines could be distinguished from those with false positives. Reduced proportion of incorrect positive predictions was correlated with higher accuracy.

The F1-Score provides an equitable evaluation of both metrics through the utilization of the harmonic mean of recall and accuracy. This number was very beneficial in maintaining a decent equilibrium between false positives and false negatives. We extensively assessed our model's performance using the F1-Score to see how well it could reduce errors and distinguish between authentic negative and positive occurrences.

As shown in Table II, our model distinguished itself among the various subtypes of migraines with excellent precision and accuracy, as well as a balanced F1-Score for each subtype. With a low probability of misclassification, the outcomes indicate that the model is capable of producing accurate predictions.

TABLE II
Accuracy, Precision, and F1-Score for Migraine Types

Migraine Type	Accuracy	Precision	F1-Score
Basilar-type aura	1.0	1.0	1.0
Familial hemiplegic migraine	0.97	1.0	1.0
Migraine without aura	0.96	0.99	1.0
Sporadic hemiplegic migraine	0.97	0.5	0.67
Typical aura with migraine	0.95	0.98	0.98
Typical aura without migraine	0.98	1.0	1.0
Other	1.0	1.0	1.0

TabNet's efficiency in migraine classification is compared to that of several other machine learning models in Table III. In relation to accuracy, precision, and F1-Score, the outcomes demonstrate that TabNet exhibits superior performance than these models. This comparison highlights the tremendous potential of the TabNet model in classifying various categories of migraines with dependability and precision.

TABLE III
Comparison with Other Models

Model	Accuracy	Precision	F1-Score
K-Nearest Neighbors (KNN)	0.6875	0.24	0.24
Logistic Regression	0.9125	0.75	0.69
Support Vector Machine (SVM)	0.7	0.17	0.14
Decision Tree	0.8625	0.54	0.56
Random Forest	0.9125	0.69	0.7
ANN	0.96	0.94	0.85
TabNet	0.98	0.99	0.98

V. Conclusion

This study employs state-of-the-art deep learning techniques, namely TabNet, to tackle the complex problem of migraine classification. In our investigations, TabNet performed very well, demonstrating high degrees of accuracy and precision in accurately identifying many migraine types. The study emphasizes the critical role that tailored and data-driven methods play in healthcare analytics, accentuating the value of medical innovation and cutting-edge research techniques.

VI. Future Scope

This study could possibly be expanded to predict drug regimens and treatment strategies devised expressly to prevent migraines. This would make patient treatment more precise and tailored. Furthermore, models like GNN might be used to forecast over-the-counter (OTC) medications for a variety of afflictions, not only migraines. These advancements might be seen as an illustration of a comprehensive approach to health management that provides patients the information they need to choose their own treatment plan.

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