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Applying Artificial Neural Networks to Determine Effective Factors on Triage Level of Digestive System Disorders in the Emergency Unit

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Abstract: Digestive system disorders are among the most frequent causes of emergency department (ED) visits worldwide and present a wide range of clinical severity. This study aimed to identify the most influential factors affecting triage levels of digestive disorders in EC using an artificial neural network (ANN) model. A cross-sectional study was conducted in one emergency unit in Mashhad, Iran. Data from 17,062 patients were extracted from the hospital information system. The findings identified several significant predictors of triage level: age, referral type, admission type, sex, insurance organization, referral month, and referral cause. The ANN model revealed that referral month and referral cause were the most impactful variables. Hematemesis was the predominant reason for urgent triage classification. Seasonal analysis indicated a higher incidence of nausea, vomiting, and diarrhea during the summer months in this city, highlighting the influence of travel and environmental factors on ED utilization. The ANN model validated conventional statistical analysis by elucidating complex interactions among predictors, demonstrating its potential to enhance patient prioritization for digestive system conditions and support ED triage decisions.

Keywords: digestive system disease, triage, constipation, diarrhea, artificial neural networks

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1. Introduction

Digestive system disorders are a significant and increasing public health issue worldwide. Lifestyle factors such as eating habits, hydration, medication use, and stress significantly contribute to the development of gastrointestinal diseases. These conditions not only impact quality of life but also place a heavy strain on healthcare systems, especially in emergency care settings [1].

Diseases of the digestive system are among the most common causes of visits to the emergency department (ED) worldwide and a huge burden on healthcare systems [2]. These disorders can lead to a variety of clinical problems including diarrhea, constipation, nausea, vomiting, and gastrointestinal bleeding. Constipation is regarded as one of the most common functional bowel disorders worldwide [3–5]. Diarrhea is another frequent functional problem associated with digestive system diseases and is the eighth most common cause of morbidity and premature death globally. It is defined as an increased frequency of bowel movements or a change in stool consistency that persists for more than 4 weeks. Its incidence in adults is 3–5% [6–8]. Vomiting is another disease that happens due to noncompliance with sanitation and healthy lifestyle and is still a serious problem according to an analysis of the 2019 National Hospital Ambulatory Medical Care Survey [9, 10]. A 2002 study estimated the cost to society of food-related and gastrointestinal infections, including vomiting, at $3.4 billion a year. This exemplifies the significant economic burden of nausea and vomiting [11]. Gastrointestinal bleeding, or hematemesis, is one of the most important digestive emergencies and is associated with high morbidity and mortality, as well as medical costs [12].

The high variability in the presentation and severity of digestive system disorders poses a major challenge in the emergency setting. Patients with similar symptoms may have vastly different underlying conditions and risk levels, making accurate triage difficult and increasing the chance of under- or over-triage. Triage is an organized approach to emergency care that groups patients according to the urgency of their clinical condition, ensuring prompt treatment for high-risk cases and efficient use of limited resources [13]. Accurate triage in emergency rooms is important for patient safety, reducing crowding, and improving clinical outcomes [14, 15]. However, establishing the correct triage level for patients presenting with digestive system complaints can be challenging, as the same symptoms may be associated with vastly different degrees of clinical severity, from benign functional disorders to life-threatening gastrointestinal bleeding [16]. Despite their critical role, traditional triage systems often face challenges due to subjectivity, variability among observers, and limited capacity to handle complex, multifactorial patient information in high-pressure emergency settings.

Artificial intelligence (AI) is increasingly used to support healthcare providers in decision-making and to improve predictive accuracy in clinical settings [16, 17]. Artificial neural networks (ANNs) have been shown to be useful in emergency medicine, where they can assist in modeling complex nonlinear associations among numerous clinical and administrative variables. Multiple studies have used machine learning to develop algorithms for triage systems in ED settings, aiming to prioritize patient care based on predicted outcomes (e.g., risk of hospitalization or disease severity). In one instance, researchers designed a machine learning algorithm using several techniques (e.g., ANNs, decision trees, and logistic regression) to predict emergency severity index (ESI-4) classifications for patients diagnosed with acute abdominal pain. The predictive capacity of the machine learning model was found to be comparable to that of physician-provided ESI-4 classifications [18]. Another study found that it was possible to develop a machine learning algorithm that used clinical, demographic, and historical patient characteristics to autonomously predict ESI classifications. The final F1-score of the machine learning algorithm was 72.2%, suggesting that the model has the potential for meaningful yet moderate predictive validity, given the challenges associated with class imbalance in the dataset [19].

Compared with traditional statistical methods, ANNs are more accurate for predicting hospital admissions, disease severity, and outcomes in the ED [20, 21]. Numerous studies have documented the emerging role of AI in triage processes in EDs, but an increasing number of studies addressing its deployment for patient triage lag; many gaps remain. Most AI research to date has focused on single clinical presentations (e.g., acute abdominal pain) and, for the most part, has relied only on clinical and physiological parameters, with very few studies analyzing broader contextual variables. Further compounding the limitations noted above is that the interrelated effects of demographic, administrative, and season-related/environmental variables on the triage determination process have yet to be fully explored. Furthermore, although machine learning models have shown promising results, their application in predicting triage levels among patients with digestive system disorders remains limited. Given the heterogeneous nature of gastrointestinal presentations and their varying levels of urgency, there is a need for more integrative models that can capture complex interactions among diverse predictors in real-world emergency settings.

This study aims to fill this gap by using an ANN model to identify the key factors affecting triage levels among patients with digestive system disorders in an ED. Specifically, it examines the importance of demographic, administrative, and seasonal variables and compares ANN modeling results with those from traditional statistical analysis. By offering a data-driven understanding of the factors that influence triage prioritization, this research could help improve decision-making and resource allocation in emergency care.

2. Materials and Methods

A cross-sectional descriptive study was conducted in a large ED in Mashhad, Iran. All patients who visited the emergency room during the study period with digestive system issues were included in the data extracted from the hospital information system (HIS). Patients' primary complaints, such as diarrhea, nausea and vomiting, constipation, and hematemesis, were used to categorize digestive system illnesses.

The triage level, which was classified according to the Emergency Severity Index (ESI), was the dependent variable. Triage levels were divided into two categories for analytical purposes:

- Urgent: ESI levels 1 and 2
- Non-urgent: ESI levels 3, 4, and 5

In line with earlier emergency triage research, this dichotomization was used to enhance model interpretability and clinical relevance.

Independent variables:

- Sex
- Age range
- Admission type (accompaniment versus pre-hospital emergency)

- Referral kind (incident versus non-incident)
- Reason for referral
- Insurance company
- Referral month

Clinical relevance and availability in the HIS database were considered when selecting these variables.

The patients' features were summarized using descriptive statistics. To identify variables significantly associated with urgent triage classification, logistic regression was employed [22]. Odds ratios (ORs) with 95% confidence intervals (CIs) were calculated. All independent variables were entered simultaneously into the logistic regression model to assess their relationship with triage level. Statistical significance was set at 0.05.

Using SPSS version 20, a multilayer perceptron (MLP) ANN was used to model nonlinear interactions between variables and triage results [23]. The components of the ANN architecture were:

- A layer of input that contains every independent variable
- Two layers that are hidden
- An output layer that shows the classification of triage (urgent vs non-urgent)

The ANN model was implemented using the MLP procedure in SPSS. The hidden layers used the hyperbolic tangent activation function, while the output layer used the softmax activation function. The number of neurons in the hidden layers and learning parameters was determined using the default optimization procedure of the SPSS MLP algorithm. To assess the model's generalizability, the dataset was split randomly into training (70%) and test (30%) sets. The model was trained for ten epochs with a learning rate of 0.001. ANNs were selected for emergency medicine because of their capacity to manage complex nonlinear interactions and their superior predictive accuracy compared to traditional statistical methods.

Receiver operating characteristic (ROC) curve analysis and classification accuracy were used to evaluate the model's performance. Model performance was evaluated using classification accuracy, sensitivity, specificity, and the area under the ROC curve (AUC). To determine each predictor's relative contribution to triage categorization, variable significance was calculated.

3. Results

A total of 17,062 patients were included in the study, with males comprising 49.4% and females 50.6%. Most patients were classified as non-urgent at triage (59.2%), while 40.8% were categorized as urgent. Most patients were admitted with accompaniment (75.4%), and most referrals were non-incident cases (99.5%).

Nausea and vomiting were the most frequent causes of referral (32.2%), followed by hematemesis (54.2%), diarrhea (5.0%), vomiting and diarrhea (5.3%), and constipation (3.3%). Most patients were between 20 and 30 years of age, and the highest number of referrals occurred during July and August (Table 1).

The distribution of referral reasons varied by gender. While hematemesis was more common in females, nausea and vomiting were the most common complaints in males. Hematemesis was more common in younger age groups, whereas nausea and vomiting were most common in individuals between the ages of 30 and 40 (Tables 2 and 3).

A seasonal study revealed significant fluctuations in referral patterns. Seasonal analysis showed variation in referral trends across different months. Hematemesis remained the most common reason for referral throughout the year, representing 54.2% of cases overall. Diarrhea and vomiting with diarrhea were more frequent during the summer months, especially in July and August, while nausea and vomiting remained relatively steady throughout the year. The highest overall referral rates were in July

Table 1. Characteristics of the population study

Variable	Variable levels	Frequency	Percentage
Triage	Urgent level	6967	40.8
	Non-urgent	10095	59.2
Sex	Male	8421	49.4
	Female	8641	50.6
Type of admission	Accompaniment	12864	75.4
	Pre-hospital emergency	4198	24.6
Type of referral	Incident	90	0.5
	Non-incident	16972	99.5
Cause of referral	Diarrhea	856	5.0
	Nausea and vomiting	5496	32.2
	Constipation	566	3.3
	Vomiting and diarrhea	900	5.3
	Hematemesis	9244	54.2
Insurance organization	No insurance	13429	78.7
	Health service	1690	9.9
	Armed services	227	1.3
	Social security	1546	9.1
	Other insurances	170	1.0

(*Continued*)

Table 1. (*Continued*)

Variable	Variable levels	Frequency	Percentage
Age	0–10 years	1717	10.06
	10–20 years	287	1.68
	20–30 years	14005	82.1
	30–40 years	1052	6.2
	>40 years	1	0.0
Referral month	April	1437	8.4
	May	1516	8.9
	June	1576	9.
	July	1697	9.9
	August	1658	9.7
	September	1507	8.8
	October	1340	7.9
	November	1316	7.7
	December	1356	7.9
	January	1318	7.7
	February	1131	6.56
	March	1210	7.1
	Total	17062	100

Table 2. Cause of referral in the population study based on sex

	Sex		
Cause of referral	Male Number (%)	Female Number (%)	TotalNumber (%)
Diarrhea	508 (6.0)	348 (4.0)	856 (5.0)
Nausea and vomiting	2725 (32.4)	2771 (32.1)	5496 (32.2)
Constipation	339 (4.0)	227 (2.6)	566 (3.3)
Vomiting and diarrhea	516 (6.1)	384 (4.4)	900 (5.3)
Hematemesis	4333 (51.5)	4911 (56.8)	9244 (54.2)
Total	8421 (100.0)	8641 (100.0)	17062 (100.0)

Table 3. Cause of referral in the population study based on age

	Age groups					
Cause of referral	0-10	10-20	20-30	30-40	>40	Total
Diarrhea	156 (9.1)	21 (7.3)	586 (4.2)	93 (8.8)	0 (0.0)	856 (5.0)
Nausea and vomiting	434 (25.3)	174 (60.6)	423 (30.2)	654 (62.2)	1 (1.82)	5496 (32.2)
Constipation	19 (1.1)	3 (1.0)	414(3.0)	130 (12.4)	0 (0.0)	566 (3.3)
Vomiting and diarrhea	225 (13.1)	36 (12.5)	573 (4.1)	66 (6.3)	0 (0.0)	900 (5.3)
Hematemesis	883 (51.4)	53 (18.5)	8199 (58.5)	109 (10.4)	0 (0.0)	9244 (54.2)
Total	1717 (100)	287 (100)	14005 (100.0)	1052 (100.0)	1 (100.0)	17062 (100.0)

(9.9%) and August (9.7%), indicating increased ED visits during the summer (Table 4).

In logistic regression analysis, sex, admission type, referral reason, insurance company, age, and referral month were significant predictors of triage level ($p < 0.05$). Compared with female patients, male patients were less likely to be categorized as urgent (OR = 0.77). Compared with patients treated by pre-hospital emergency services, those admitted with accompaniment were less likely to be classified as urgent (OR = 0.59).

The strongest correlation with triage classification was the cause of referral. All other digestive problems were much less likely to be classified as urgent than hematemesis. Patients without insurance were far more likely to be classified as urgent triage (OR = 5.39).

Additionally, there was a substantial correlation between age and triage level; younger age groups were less likely to be classified as urgent. Strong seasonal effects were observed in the referral month, with October having the highest probability of urgent triage compared with March (OR = 3.77) (Table 5).

The ANN model validated the significance of several criteria in determining triage levels. According to variable importance analysis, the most significant predictor was the referral reason,

Table 4. The cause of referrals in the population study is based on the referral months

	Referral month												
Cause of referral	April	May	June	July	August	September	October	November	December	January	February	March	Total
Diarrhea	58 (4.0)	62 (4.1)	77 (4.9)	135 (8.0)	86 (5.2)	86 (5.7)	87 (6.5)	73 (5.5)	74 (5.5)	38 (2.9)	40 (3.5)	40 (3.3)	856 (5.0)
Nausea and vomiting	509 (35.4)	446 (29.4)	516 (32.7)	536 (31.6)	552 (33.3)	512 (34.0)	422 (31.5)	499 (37.9)	472 (34.8)	379 (28.8)	288 (25.5)	365 (30.2)	5496 (32.2)
Constipation	62 (4.3)	75 (4.9)	54 (3.4)	53 (3.1)	54 (3.3)	30 (2.0)	44 (3.3)	36 (2.7)	55 (4.1)	31 (2.4)	29 (2.6)	43 (3.6)	566 (3.3)
Vomiting and diarrhea	48 (3.3)	51 (3.4)	62 (3.9)	160 (9.4)	113 (6.8)	124 (8.2)	111 (8.3)	75 (5.7)	70 (5.2)	47 (3.6)	23 (2.0)	16 (1.3)	900 (5.3)
Hematemesis	760 (52.9)	882 (58.2)	867 (55.0)	813 (47.9)	853 (51.4)	755 (50.1)	676 (50.4)	633 (48.1)	685 (50.5)	823 (62.4)	751 (66.4)	746 (61.7)	9244 (54.2)
Total	1437 (100.0)	1516 (100.0)	1576 (100.0)	1697 (100.0)	1658 (100.0)	1507 (100.0)	1340 (100.0)	1316 (100.0)	1356 (100.0)	1318 (100.0)	1131 (100.0)	1210 (100.0)	17062 (100.0)

Table 5. Effective factors on the level of triage

					95.0% CI for OR		
Variable	Variable levels	B	S.E	OR	Lower	Upper	p value
Sex	Male	–0.261	0.045	0.770	0.705	0.841	0.000
Type of admission	Accompaniment	–0.524	0.050	0.592	0.537	0.653	0.000
Type of referral	Incident	0.004	0.275	1.004	0.586	1.721	0.989
							0.000
cause of referral	Diarrhea	–3.976	0.198	0.019	0.013	0.028	0.000
	Nausea and vomiting	–3.232	0.068	0.039	0.035	0.045	0.000
	Constipation	–5.702	0.584	0.003	0.001	0.010	0.000
	Vomiting and diarrhea	–3.506	0.149	0.030	0.022	0.040	0.000
							0.000
Insurance organization	No insurance	1.684	0.453	5.389	2.216	13.104	0.000
	Health service	–0.354	0.483	0.702	0.273	1.808	0.464
	Armed services	–0.331	0.619	0.718	0.214	2.413	0.592
	Social security	–0.574	0.492	0.563	0.215	1.479	0.244
							0.000
Age	0–10 years	–0.426	0.130	0.653	0.507	0.842	0.001
	10–20 years	–1.074	0.242	0.342	0.213	0.549	0.000
	20–30 years	–0.757	0.114	0.469	0.375	0.587	0.000
							0.000
Referral month	April	0.588	0.104	1.801	1.468	2.209	0.000
	May	1.029	0.105	2.797	2.278	3.434	0.000
	June	1.040	0.104	2.829	2.307	3.470	0.000
	July	1.269	0.106	3.557	2.888	4.381	0.000
	August	1.197	0.105	3.312	2.697	4.066	0.000
	September	1.000	0.106	2.718	2.208	3.346	0.000
	October	1.328	0.112	3.774	3.028	4.702	0.000
	November	0.859	0.110	2.361	1.903	2.929	0.000
	December	0.992	0.110	2.698	2.176	3.344	0.000
	January	–0.904	0.101	0.405	0.332	0.494	0.000
	February	–1.044	0.105	0.352	0.287	0.432	0.000

CI: confidence interval, OR: odds ratio, B: logistic regression coefficient, S.E.: standard error

followed by referral month, insurance company, and age. Sex and admission type contributed less but remained significant to model performance (Table 6, Figure 1).

The ROC curve analysis demonstrated that the ANN model had strong discriminative performance for distinguishing urgent from non-urgent triage categories, with an overall area under the curve (AUC) of approximately 0.90 (Figure 2). The ROC curves in the figure were automatically generated by SPSS for each class within the same binary classification model; however, the reported AUC represents the overall classification performance of the ANN model.

4. Discussion

The current study used both logistic regression and ANN models to examine the factors influencing triage levels among

Table 6. Affecting coefficients upon triage

Variables	Independent variable importance	
	Importance	Normalized importance (%)
Sex	0.024	7.1
Type of admission	0.041	12.4
Type of referral	0.055	16.7
Cause of referral	0.330	100.0
Insurance organization	0.132	40.0
Age	0.130	39.5
Referral month	0.289	87.8

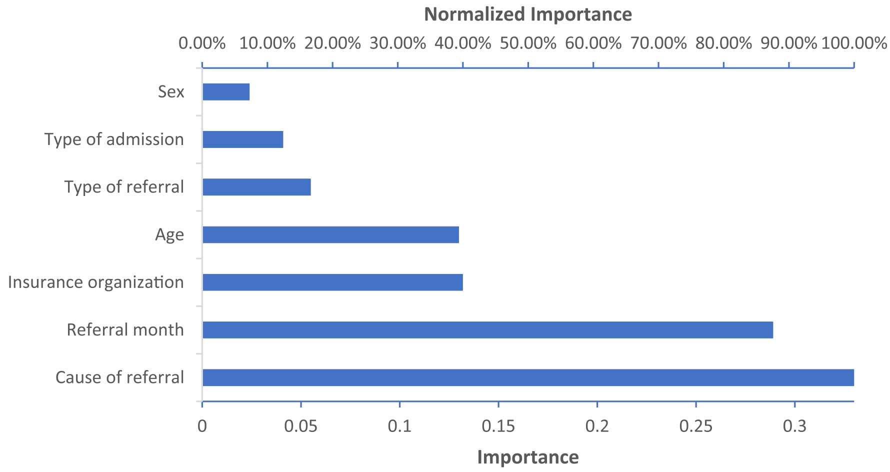

Figure 1. Affecting coefficients upon triage

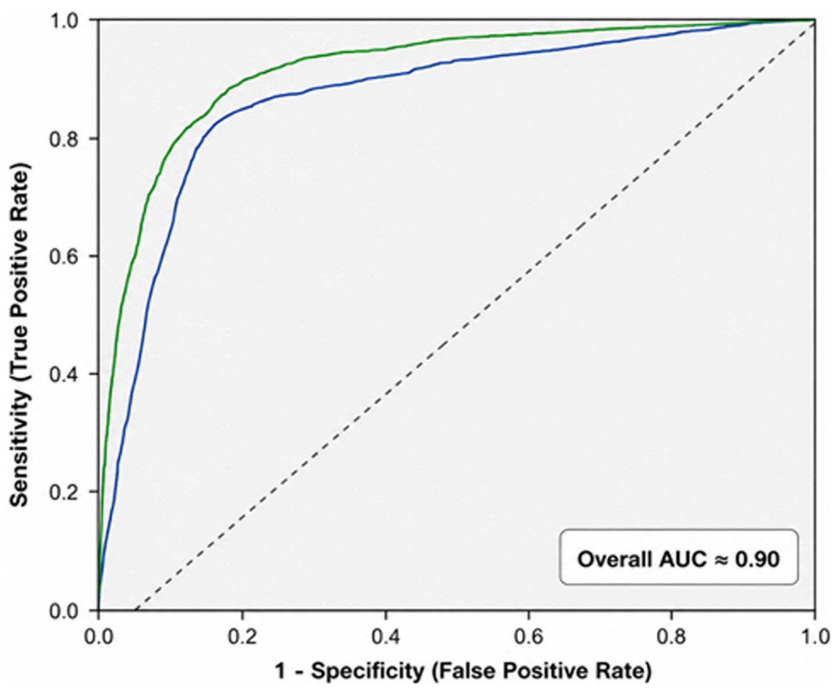

Figure 2. Receiver operating characteristic (ROC) curves demonstrating the performance of the ANN model in distinguishing urgent versus non-urgent triage categories. The two curves represent class-specific visualizations automatically generated by SPSS within the same binary classification model, while the reported AUC (≈0.90) reflects the overall discriminative performance of the ANN model.

patients with digestive system problems in an emergency room. The results showed that triage decision-making is influenced by a combination of clinical, demographic, and administrative factors, with referral cause emerging as the most influential predictor. These results highlight the multifactorial nature of triage processes and underscore the added value of ANN models in capturing complex and nonlinear relationships among predictors.

Hematemesis emerged as the most significant predictor of urgent triage classification, which is expected given its strong link to hemodynamic instability and life-threatening complications. This finding aligns with previous studies that identify gastrointestinal bleeding as a high-risk emergency condition requiring immediate intervention. Importantly, this result supports the model's clinical validity and demonstrates its ability to accurately detect critical cases in emergency settings [12]. The prevalence of hematemesis in urgent triage categories underscores the need to promptly identify and treat these individuals.

In addition to emergency management, these findings also highlight the importance of preventive strategies targeting gastrointestinal disorders. Unhealthy dietary habits, poor nutrition, and inadequate lifestyle behaviors are recognized contributors to gastrointestinal bleeding and related digestive complications. Therefore, public health interventions focusing on nutritional education, physical activity, and healthier dietary patterns may help reduce the burden of severe gastrointestinal conditions requiring emergency care.

Another important factor influencing triage levels was seasonal change. Diarrhea, vomiting, and other gastrointestinal symptoms are more common in the summer, consistent with previous research linking increased gastrointestinal illnesses to travel, contaminated food, and poor hygiene [24]. Population density, nutritional variations, and environmental exposures may amplify these seasonal effects in pilgrimage cities like Mashhad, thereby affecting ED workload and triage patterns.

The high frequency of diarrhea and vomiting, particularly among children and adolescents during warmer seasons, further emphasizes the need for targeted healthcare planning and preventive strategies. Educational interventions aimed at improving food hygiene, hydration practices, and nutritional awareness may contribute to reducing avoidable ED visits related to gastrointestinal infections and seasonal digestive illnesses.

Additionally, there was a substantial correlation between age and triage classification. While older age groups were more susceptible to severe digestive disorders, younger patients had a reduced likelihood of urgent triage. This finding is consistent with earlier research showing that older persons are more likely to experience constipation, gastrointestinal bleeding, and consequences associated with comorbidities [3, 5, 25]. These findings emphasize the importance of factoring in age during triage decisions.

One significant administrative factor affecting triage level was the insurance organization. Patients without insurance were more likely to be categorized as urgent, possibly due to higher illness severity at presentation, reduced access to preventive care, and delayed healthcare-seeking behavior. Previous research has found similar correlations between insurance status and emergency utilization [26, 27], indicating that socioeconomic factors remain important determinants of emergency care patterns.

The logistic regression results were validated and extended by the ANN model, which illustrated the intricate nonlinear relationships among the predictors. The insurance company, referral month, and cause of referral were identified by ANN as the most significant factors in triage prediction. These findings align with earlier research showing that ANN models outperform conventional statistical methods in emergency medical applications [16, 20, 21]. ANNs' applicability for triage decision-support systems is enhanced by their ability to capture nonlinear interactions.

However, despite these advantages, ANNs also have certain limitations. ANN models may be less interpretable than traditional statistical models, making it harder to directly explain the influence of individual predictors. Additionally, complex models like ANNs can be prone to overfitting. In this study, this risk was partially reduced by splitting the dataset into training and test subsets and by comparing ANN findings with logistic regression results. Nevertheless, the retrospective design and reliance on HIS data limited access to important clinical variables such as vital signs, laboratory findings, and comorbidity profiles, which may further improve predictive performance. Furthermore, because the study was conducted in a single referral center, the generalizability of the findings may be limited. Future multicenter studies incorporating physiological and laboratory parameters, along with external validation and cross-validation techniques, are recommended to improve the robustness and applicability of AI-based triage prediction models.

Overall, this study demonstrates that ANN models can effectively identify key determinants of triage levels in patients with digestive system disorders by integrating clinical, demographic, administrative, and temporal factors. The findings highlight the importance of adopting data-driven approaches to better capture the complexity of triage decision-making in EDs. By incorporating diverse predictors and modeling their nonlinear interactions, AI-based systems can improve triage accuracy, support clinical decision-making, and enhance resource allocation in high-demand healthcare settings.

5. Conclusion

The most significant determinants of triage level among patients with digestive system illnesses in the emergency room were age, insurance organization, referral month, and referral cause. The most common cause of urgent triage classification was hematemesis, highlighting the crucial role gastrointestinal bleeding plays in emergency triage prioritization.

The results of conventional statistical analysis were validated by the ANN model, which demonstrated a strong ability to capture intricate interactions among predictors. These findings lend credence to the possible use of intelligent predictive algorithms to improve ED productivity and triage accuracy.

To enhance model generalizability and practical application, multicenter research with a broader range of clinical parameters is advised.

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Ethical Statement

The Ethics Committee of Mashhad University of Medical Sciences approved this project under the code of IR.MUMS.MEDICAL.REC.1397.171. All information was gathered in hindsight from standard clinical records. Data confidentiality was rigorously upheld throughout the study, and informed consent was acquired at admission.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support this work are available upon reasonable request to the corresponding author.

Author Contribution Statement

Zakiyeh Balouchzehi: Writing – original draft, Writing – review & editing, Visualization. **Mohaddeseh Badpeyma:** Writing – original draft, Writing – review & editing, Visualization. **Tahmineh Aldaghi:** Writing – original draft, Writing – review & editing, Visualization, Project administration. **Hamed Tabesh:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources. **Reza Akhavan:** Software, Data curation. **Zahra Ebnehoseini:** Validation, Formal analysis, Investigation, Resources. **Elham Nazari:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition.

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