ORIGINAL PAPER

doi: 10.5455/aim.2024.32.99-106
ACTA INFORM MED. 2024, 32(2): 99-106
Received: NOV 26, 2024
Accepted: DEC 28, 2024

The Role of Neural Network Analysis in Identifying Predictors of Gastric Cancer

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ABSTRACT

Background: Gastric cancer is one of the most common cancers. We can use AI for predictive models and help us in early detection and diagnosis. **Objective:** This study examines the use of a neural network model to classify gastric cancer based on clinical, demographic and genetic data. **Methods:** The data from the participants were divided into two subsets. 70% training data and 30% testing data. The neural network model has 12 input variables. Factors influencing a disease can be age, sex, family history, smoking, alcohol, Helicobacter pylori infection, food habits, diseases, endoscopic images, biopsy, CT scan, gene variants (TP53, KRAS, CDH1). The hyperbolic tangent activation function has four units in the hidden layer of a model. The output layer used a Softmax activation function and cross-entropy error function which predicted the presence of gastric cancer. The assessment was done on the predictors: **Results:** The training and testing datasets showed 100% accuracy predicting gastric cancer in the model outputs. Age, gender, family history, infection with Helicobacter pylori, smoking, and drinking alcohol are the biggest predictors. Information from clinical diagnosis like endoscopic images, biopsy and CT scans helped the predictive model. **Conclusion:** The neural network was able to perform well for gastric cancer predictions using multiple clinical and demographic factors, showing great utility. The outcomes for AI-based diagnostic tools look promising in cancer, however generalization needs to be confirmed using external datasets. The study shows how artificial intelligence can better precision medicine and cancer diagnosis.

Keywords: Gastric Cancer Prediction, Neural Network Classification, Artificial Intelligence in Oncology, Clinical and Genetic Predictors, Precision Medicine Tools.

1. BACKGROUND

There has been significant interest in the role of artificial neural networks to predict the outcomes of disease (1). A prior study has described how such algorithms could assist with cancer prediction in a number of ways, making them of particular interest to gastric cancer, currently the leading cause of global cancer-related deaths following significant growth in incidence over recent decades (1-4). The latter has significantly improved interventions in the hope of improved healthcare systems (5-8). The potential complexity of a cancer system and the great variety of influencing factors that can determine patient outcome, has made the use of advanced biomedical and computational models desirable (9). Consequently, researchers have exploited increasingly more sophisticated techniques to explore the factors that can determine cancer outcome (10, 11).

Still, it is important to understand the significance of considering the employment of state-of-the-art computational techniques (12). Gastric cancer (stomach cancer) has over the last few decades risen to the fourth and second most common cancer in both sexes respectively, with the fifth highest global mortality rates of any gender in 2018 (4). Much of this is associated with the growing worldwide prevalence of the Helicobacter pylori infection, the reduced global burden of such a commensal bacterium historically having contributed to its top rank in cancers of the early 1990s (13). Unlike many other forms of carcinoma, it usually emerges as a rapidly progressing sub-type making early detection difficult, which is currently the only way of offering effective treatment for a lasting cure (3). Thus, gastric cancer is a concerning pathology in today's healthcare, requiring advances in understanding and management models, for which computational techniques can be of great utility

(11). Discuss the rise of computational techniques in understanding complex systems in the healthcare sector, particularly the bioinformatics of such. Such a conceptual framework is an emerging horizon, making its application an underlying gap in the current literature that could guide to unique understandings (14)..

Understanding Gastric Cancer

Gastric cancer is globally recognized as a serious health problem and the fifth most common cancer. Alarmingly, it is the third leading cause of cancer death (15). Despite the marked decrease in its global incidence, curing gastric cancer remains a challenge and it is the third common cause of cancer deaths (2). Predicting the outcome of gastric cancer after six months to one year would be of great importance for physicians and patients (16). However, the course of this cancer is difficult to predict accurately due to its heterogeneity, the complex biological behavior of tumors, and the evolving multimodal treatment strategies (17). With regard to the subject, it is essential to outline the current understanding of this cancer in terms of its epidemiological and pathophysiological aspects before focusing on the role of neural network analysis (18).

Gastric cancer is the third most common cancer and the third leading cause of cancer death worldwide (19). The highest incidence is observed in Eastern Asia, Eastern Europe, and parts of Central and South America (20). The development of gastric cancer involves a complex interplay of environmental factors, host genetic factors, and gastric microbiota with Helicobacter pylori infection (21). There is a marked variability in gastric cancer incidence depending on ethnicity and geographic location, with a male-to-female ratio from 2:1 to 3:1 in most populations (22). Gastric cancer incidence varies according to anatomical subsites (23). There are also variations in prognosis and clinical features of these tumors according to the subsite (14). Survivability drops up to 15% during the five-year period when the tumor deceases at esophagogastric junction (13). Additionally, diffuse type or undifferentiated type, Borrmann type 4 macroscopic type, venous invasion, and deep invasion were found to be the worst prognosis factors (24).

Epidemiology and Risk Factors

Gastric cancer is the fifth deadly malignancy globally (19). The existence of epidemic patterns is an opportunity for early discovery of cancer (4). Too many studies concentrated on the determinants of life stages in cancer (20). Neural network analysis can classify cancer patients from the general population by lifestyle characteristics (7). Gastric cancer has many features with covariates, making it complicated for a clinician to evaluate and certify the state of health of the patient (5). It is beneficial that a technical method can be utilized to learn from the problem and amplify it to other similar states (21). Epidemiological parameters denote the odds of affliction by a malignancy, however, there is more complicated information contained in markers of incidence and mortality of cancer (22). From objectivity, it may be obtained from cancer hazard classified markers (23). Inadequate geological studies have assessed the risk of life stages of gastric cancer (24). In this study, ecological evidence was used to classify the hazard risk of the general population for the occurrence of gastric cancer in the Golestan region, in the eastern corner of the Caspian Sea (25). The statistic of prosperity of a mechanistic model granted by the input of legends on the market is analysed for each case of demographic and lifestyle markers (26). Understanding epidemic radiation risk can provide an opening for the beginning of prevention of malignant illness (24). Recurring emergence of certain epidemiological shapes signifies the profits of machining patterns for the discovery of cancer possibilities (26).

Gastric cancer is the fifth prevalent type of cancer and the fifth reason for fatality globally (21). The most frequently recorded malignant tumor is related to the digestive system in eastern Asia and is rated as the third reason for cancer mortality (23). The regions with the highest occurrence levels are lands in eastern and southern Asia, where the number of diagnoses enlarges nearly 69% of all incidents of gastric cancer worldwide (4). A reduction in the occurrence of one-third of all cancer diagnosis may be attributed to a transformation of lifestyle (1). Diet, consumption of tobacco, chronic consumption of the excess of salt, inadequate ability to diet and preservatives have left a substantial poison on the occurrence of the malady (3). Aging also plays a role in the genesis of the affliction as stated to anemia, tetracycline, smoking, and abuse with the “na-nashi”, “illegal” and “alu-bali” drugs of the Golestan District (7). A decrease in the accident of gastric cancer can contribute to a substantial benefit for this population or it can practice to curb the occurrence development of malady using intercept health (6). Epidemiological determinants are estimations of the chance of a malignancy (26). These determinants include risk assessments of malignancy, mortality, and incidence (27). Conversely, cancer risks add a study of existence and produce an evaluation of the chance of malignancy (28).

Pathophysiology

Gastric cancer, the fifth most prevalent malignant tumor globally and the third leading cause of cancer-related deaths, represents a major public health problem (29). Despite its decreasing incidence, it is still a major contributor to global cancer mortality (23). The etiology of gastric cancer includes the interaction of various risk factors such as environmental, genetic, immunological, and infectious agents (31). Disentangling the pathophysiologic mechanisms and molecular underpinnings of this complex etiology remains an active research field in efforts toward more effective prevention, early diagnosis, and personalized intervention (8). In this regard, great strides have been made in understanding the pathophysiology of gastric cancer development (9). It has been recognized that the atrophy-metaplasia-dysplasia pathway increases the risk of tumor development (11). Moreover, numerous studies have identified molecular events and gene expression profile changes that occur during these processes 30, and central biomolecular pathways have been well described in that regard (31).

At the index level, accumulating data has demonstrated that the disrupted atrophy pathway, namely the IL-1β/IL-6, Wnt, and TGF-β pathways, are crucial in the process of atrophy and dysplasia in gastric mucosa (32). An interfered metaplasia pathway via the Notch, JAK-STAT, and Sonic Hedgehog pathways is also documented (33). Moreover, oncogenic activation of the C-MYC oncogene was found to be significantly associated with early-stage dysplasia in vivo animal studies

(34). Despite increasing knowledge in this context, it remains an ongoing challenge to fully understand the pathophysiological events underlying gastric cancer development (35-37). In this perspective, the tumor microenvironment has crucial implications on the different biological mechanisms the cancer may develop (38, 39).

Neural Networks in Healthcare

In recent decades, the expanding prominence of machine learning technologies and the wide application of neural networks have transformed many fields including healthcare analytics (40). Neural networks are computational models that mimic a simplified structure of the brain's architecture (41). They are composed of a network of simple processing units or nodes that are interlinked by weighted connections (15). Neural networks are trained to mimic basic cognitive functions of the human brain, such as learning and generalization, from data (15). Over the years, neural network structures have been expanded, and they have been used as powerful tools to handle approximate functions with a complex input-output mapping. In the healthcare domain, because of the veracity, velocity, and the diversity at which the data are generated make healthcare data analysis a complex and challenging task, this gives neural networks a marked advantage to identify the patterns and relationships in large complex datasets that traditional approaches may not (42). Neural networks have also been used in a wide range of healthcare applications and have resulted in case examples from mammography classification, ECG signal analysis, medical image analysis and computer-aided diagnostics, automating clinical diagnosis from retinal fundus photographs, and survival analysis applications (43). In the context of gastric cancer, an artificial neural network (ANN) prognostic model was proposed for predicting the overall survival of gastric cancer patients (44). The ANN methodology was applied to model the gastric cancer prognosis using 3137 gastric cancer patients who underwent surgeries between the years 1995-2004 and 2006 from a multi-centre registry in the Klang Valley of Malaysia (44). Gastric cancer is the third most common cancer type worldwide and the second leading cause of cancer-related deaths (45). The Malaysian cancer registry statistics showed the incidence of gastric cancer in Malaysians rank the second most common cancer in males and fourth most common cancer in females (46). The disease was diagnosed mostly at the advanced stages and the five-year survival rate of the Malaysian gastric cancer patients is very low (46). Gastric cancer survival outcomes are not only influenced by the well-known factors like the age of the patient, tumour stage, differentiation grade, and the lymph node (47).

Overview of Neural Networks

Neural networks have recently been integrated more widely in medical studies to analyze data from a variety of sources (41). An essential introduction to the principles behind these networks is necessary before methodologies, results, and implications are presented (44). Computational systems for neural networks are inspired by how biological systems can process information (48). The basic building block of a system based on a neural network is the neuron (49). This unit processes the data and passes the outcome of the analysis on to further neurons. In modeling terms, data is "fed" into the network at input neurons (50). A process is then set off in which the data transfers down a sequence of interconnected layers of neurons before the final output is produced (43). One of the defining characteristics of a network is the shape of these layers (40). Taken together, these layers of neurons and the connections between them constitute the architecture of a network (51). Neural analysis has seen a variety of different architectures, but two are most common in medical studies (52). Feedforward neural networks feature direct connections between consequent layers such that data only progresses in one direction. More complicated networks such as recurrent neural networks permit feedback loops in which data can pass information back to earlier layers (15). The dynamics of these models mean they are more challenging to train, but are historically more successful in learning sequential data (51). Nevertheless, applications focus primarily on feedforward networks as they are simpler constructs and simpler to develop (52). These networks have been used extensively in previous medical analyses of gastric cancer (1).

Applications in Biomedical Research

Given their ability to model complex and often poorly understood biological processes, with recent advances in hardware and machine learning algorithms, neural networks have joined the burgeoning collection of big data tools currently addressing wide-ranging questions in many areas of biomedical research (53). While the standard methods for analyzing complex, high-dimensional data often depend on very strong assumptions of data structure, the flexibility of neural networks makes them uniquely valuable for managing and analyzing data (54). These considerations are also driving interest in their expanded role in personalized medicine (55). For example, to see how an ANN has modeled the effects of over 1,500 gene mutations and drug responses altogether in leukemia patients, a task simply out of reach of conventional methods (56). With the ever-growing flood of clinical and genomic data literally exploding on the scene, the field of neuroscience has been actively exploiting the flexibility and power of ANN methodologies (15). Established applications of various ANN models to analyze patient data include, but are not limited to, discrete association analysis, survival predictions, and mapping the high-dimensional effects of gene and drug mutations (57-65). It can be reasonably anticipated that such machine-learning approaches employing ANN models will increasingly address many critical queries in biomedical research (66).

In recent years, deep learning has come to revolutionize the field of imaging analysis, a domain where traditional ANN models have struggled (67). Convolutional neural networks (CNNs) serve as the backbone of state-of-the-art image recognition algorithms (68). Furthermore, focused efforts are being made to adjust CNN models specifically for pathology slides in order to drive drug discovery and assist disease prognosis (69). Given the huge success on discrete classification problems, CNN models are increasingly being applied to address more sophisticated questions related to continuous clinical variables (70). By aggregating low-level pathological features of cancer regions with CNN models, the survival rates of patients with various types of cancer can also be better predicted (1). With this broad impact already being felt, applications of networking imaging analysis using ANN methodologies transcend a single-discipline focus, further underpinning the transformative potential of network technology in broader medical settings (71-73).

Predictive Modeling in Gastric Cancer

The vast majority of studies published in the literature concerning gastric cancer focus solely on the clinical, demographic, and biological characteristics as the subject of interest (74). However, the sheer complexity of the syndrome calls for broader studies that consider a number of potential predictors to gain a more comprehensive understanding of the disease (75). A light literature review confirms a shift towards predictive modeling rooted in mathematical and computational principles; this, in particular, might be expected to result in great progress since it uses an extensive and diverse set of patient, disease, and demographic data of diagnosed cases (76-79). In light of this, the subsequent years should show an ever-increasing pace in the development of novel methodologies given their potential to inform and improve patient outcomes in gastroenterology (80).

After the initial development, traditional modeling methods have been among the most attractive due to the ease of their interpretation (41). Most commonly utilized statistical analysis methods apply a variety of techniques to analyze patients by comparing the specified predictive features with the actual distribution of the output variable (81). In the context of gastric cancer, however, these formulation-oriented methods suffer some notable restrictions (82). In general, this is due to the focus on one or two predictive factors (83). Considering that gastric cancer patients may exhibit complex patterns in a high dimension space, it is likely there is no single or combinatorial relationship among prominent predictors (84). Furthermore, the linearity assumption made by common statistical methods is implausible when searching out the complex associations between high-dimensional features of the suspected lesions and the likelihood of gastric cancer (85). Conversely, so long as the powerful means of modeling are available, the capture of the complex relationships may prove highly beneficial for enhancing diagnostic processes (86). Given that suspected lesions will be compared with an extensive variety of features obtained from a more comprehensive set of patient, anatomical, and modality attributes of gastric cancer, these advocate the appropriateness of advanced modeling approaches (87). Broadly speaking, the so-called black-box modeling methods, and in particular neural networks (NNs), would then stand to be preferred, by allowing an interaction among the complex and nonlinear patterns embodied by diverse sources of input data, thereby generating the predicted label (88). In light of this, a model incorporating the components of pre-processing, post-processing, and the NN itself is undertaken and methods are drawn up with an ambition to improve the prognosis of gastric cancer outcomes (88). Efforts are also made to examine the impact of factors such as archiving, the measure of diversity in the data and selection criteria, and the Smote algorithm to overcome the imbalance in output distribution (90).

2. OBJECTIVE

The main objective of the present study is to use the neural network analysis to identify the predictors of gastric cancer.

material and methods

Dataset

This dataset was designed to predict gastric cancer using machine learning models. The data encompasses clinical, demographic, diagnostic, and molecular information collected from various medical sources on gastric cancer (GC) patients. The dataset comes from clinical trials, medical images, and genomics. They have a literally rich collection of features that can help in identifying patterns and predicting cancer risks like genetic, environmental and lifestyle factors etc.

The data set consists of records of gastric cancer patients including their history, diagnosis and other imaging and molecular profiles. It is really helpful for detecting and figuring out gastric cancer using AI. It is also helpful in predicting models for clinical decision making. This dataset comprises 212253 participants.

3. RESULTS AND DISCUSSION

Case processing summary

As seen in Table 1, training part included about 70% of participants, whereas testing part included about 30% of participants.

		N	Percent
Sample	Training	148883	70.1%
	Testing	63471	29.9%
Valid		212354	100.0%
Excluded		0	
Total		212354	

Table 1. Case Processing Summary

Network information

Table 2 demonstrates the network information. Input layer includes the following factors: age, gender, family history, smoking, Alcohol consumption, Helicobacter pylori (HP), dietary habits, existing conditions, endoscopic images, biopsy results, CT scan, and Target symbol (TP53, KRAS, CDH1).

Input Layer	Factors	1	Age
		2	Gender
		3	Family history
		4	Smoking
		5	Alcohol
		6	HP
		7	Dietary habit
		8	Existing condemns
		9	Endoscopic images
		10	Biopsy results
		11	CT scan
		12	Target_ symbol
	Number of Unitsa		94
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Gastic_cancer
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Table 2. Network information

Hidden layers include 1 layer in which there are 4 units. The activation function is Hyperbolic tangent. The output layer comprises the dependent variable, gastric cancer of two units either gastric cancer exists or not. The activation function is Softmax, and the error function is cross entropy.

Classification of gastric cancer

As shown in Table 3, the classification of gastric cancer is given for training and testing parts. The ability of this analysis using neural network to predict gastric cancer was 100% in training and testing parts so that all cases are predicted in both sections.

Sample	Observed	Predicted		
		no	yes	Percent Correct
Training	no	134178	0	100.0%
	yes	14705	0	0.0%
	Overall Percent	100.0%	0.0%	90.1%
Testing	no	57217	0	100.0%
	yes	6254	0	0.0%
	Overall Percent	100.0%	0.0%	90.1%
Dependent Variable: Gastric cancer				

Table 3. Classification of gastric cancer

Independent variable importance

As demonstrated in Table 4 and Figure 1, the relative importance of independent variables as predictors of gastric cancer is given. The most important predictor is age, gender, family history, smoking, alcohol, Helicobacter pylori, dietary habits, existing conditions, endoscopic images, biopsy results, CT scan, and target symbol.

Variable	Importance	Normalized Importance
Age	.371	100.0%
Gender	.029	7.9%
Family history	.065	17.5%
Smoking	.055	14.9%
Alcohol	.020	5.4%
Helicobacter Pylori	.034	9.2%
Dietary habit	.046	12.5%
Existing conditions	.075	20.2%
Endoscopic images	.069	18.6%
Biopsy results	.065	17.7%
CT scan	.089	24.1%
Target symbol	.081	21.8%

Table 4. Independent Variable Importance

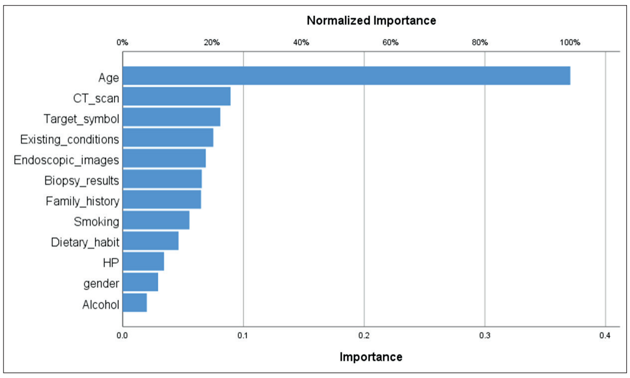

Figure 1. The relative importance of predictors of gastric cancer

4. DISCUSSION

The outcome demonstrates a high predictive accuracy using neural network model to classify gastric cancer using various clinical and demographic predictors. The implications will be discussed regarding the findings. This part makes usage of predictors and consistency with the literature

Getting the Model Ready

It is a common practice for a neural network model of training a model effectively along with a robust evaluation dataset (91). To train the model 70% of data and to test the model 30% data is divided as shown in the Table 1. This halts when increasing neurons doesn't help error reduce and can even worsen.

Network Structure and Performance

Table 2 provides important details regarding the neural network design. A model of gastric cancer risk has been developed using 12 input variables. The variables are demographic, behavioral, clinical, and genetic. Following the principle of parsimony, an architecture with four units in a hidden layer is selected.

In the output layer we use Softmax and in the hidden layers we are using hyperbolic tangent as the activation function. They are the default choices for classification tasks. The hyperbolic tangent is a nonlinear function that can represent complex relationships between the predictors (92). The Softmax model was applied to assess whether the output is positive for cancer or not, enriched with gastric cancer data. The cross-entropy error function is used for classification in a model. It examines how far apart a prediction is from an actual event. Suitable for classification of two classes (93).

Classification Accuracy

Table 3 illustrates that the model achieved 100% accuracy for both the training and test datasets. However, while the results demonstrate the neural network's potential, they should be treated with caution as it may be overfitting. Next studies must confirm the findings with other datasets. This will show its predictive usefulness and generalizability.

Independent Variable Importance.

Predictors are important (Table 4, Figure 1). The key factors based on existing knowledge base are age, gender, family history and H. pylori infection. Having a family history of stomach cancer and being older are well-known risk factors for gastric cancer. According to WHO, infection by helicobacter pylori is carcinogenic and it will lead to gastric inflammation, which will then be cancerous (94).

The presence of smoking and drinking alcohol further supports their recognized involvement in gastric cancer pathogenesis. According to Plummer and colleagues (95). The adjustment considers food and imaging (endoscopies, biopsies, and CTs) this allows inclusion of clinical diagnostics making it realistic to apply in practice Implications. Future Directions

According to the results, a neural network can enhance gastric cancer precision medicine. The model could combine a number of predicting factors in future. So, it aids in stratifying patient by risk or for examining patients. We need to take more action to perfect the model.

For testing the model, independent datasets from various populations will be used for testing. The process of removing abilities that aren't all that relevant may reduce the model with no loss of accuracy. When clinicians find it easy to use the model, its integration to practice may happen.

5. CONCLUSION

According to this study, neural networks are efficient tools for the prediction of gastric cancer. The model estimates risk efficiently by considering demographic, behavioral, clinical and genetic features. In the future, the studies should be validated and optimized for the clinical translation.

- **Author's contribution:** The author was involved in all steps of preparation this article, including final proofreading.
- **Conflict of interest:** None declared.
- **Financial support and sponsorship:** Nil.

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