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RESEARCH ARTICLE

Deep Learning Framework for Colorectal Cancer Classification Using ResNet18 Based on Dietary Habits Related to Meat Intake and Cooking Methods

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ABSTRACT Abstract Colorectal cancer (CRC) is a serious health problem globally, needing early identification for optimal treatment. Ingestion of mutagens such as heterocyclic amines (HCA), which are produced when meat is cooked at high temperatures, is believed to increase the risk of colorectal cancer. The present study's objective was to investigate the relationship between different meats cooked at different temperatures and CRC formation. Automated colorectal cancer detection methods that analyze regular dietary patterns will aid clinicians. This study employed the PLCO dataset of 1,54,892 individuals aged 55 to 74 (76,679 men and 78,213 females). A deep learning framework was designed with a classification and prediction phase. Two distinctive methods were applied to categorize meats cooked by various cooking methods in the Resnet18 (convolutional 1D) model. In the first approach, we uploaded the complete dataset for classification, whereas the second separated them into 30 segments and tested them. The prediction layer then predicted cancer patients' ages. The classification and prediction layers were created using Resnet18 (convolutional 1D) with the Root Mean Squared Propagation (RMSProp) and Adam optimizers. We estimated risk ratios (RR) with 95% confidence intervals (CI) for the association between meat intake or cooking style and CRC risk. Our primary finding was a positive link with CRC for pan-fried hamburgers (RR: 1.86, CI: 1.09-3.18) and bacon (RR: 1.1, CI: 0.79-1.53), while a negative relationship was detected between pan-fried chicken (RR: 0.8, CI: 0.51-1.27) and beef steak (RR: 0.43, CI: 0.06-3.01). The broiled chicken intake (RR: 0.8, CI: 0.78-1.67) decreased CRC risks, but broiled beef steak (RR: 1.46, CI: 0.96-2.24) and meat (RR: 1.25, CI: 0.98-1.60) have statistically elevated the CRC risk. Grilled or barbecued hamburgers (RR: 2.06, CI: 0.79-3.42) and beef steaks (RR: 1.31; CI: 0.76-2.25) showed a favorable connection with CRC. Meanwhile, adverse associations were found between grilled or barbecued poultry (RR: 0.84, CI: 0.52-1.34) and pork chops (RR: 0.46, CI: 0.11-1.82). Pan-fried hamburgers and bacon, broiled and barbecued beef steak may be involved in the etiology of colorectal cancer.

INDEX TERMS Deep learning, ResNet-18, colorectal cancer, meat cooking methods, heterocyclic amines.

I. INTRODUCTION

Studying genetic defects in cancer cells has yielded critical insights into the processes that drive cell development over the past few decades. In that, cooking methods' effect on factors promoting malignant cell formation remains largely unexplored [1]. Cancer remains a severe and alarming health issue despite living in an advanced and technologically sophisticated world [2]. Cancer accounted for 10.3 million deaths and 19.3 million new cases worldwide in 2020, as reported by the World Health Organization (WHO) [3]. According to the Global Cancer Laboratory (GCO) and the

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International Agency for Research on Cancer (IARC) [4], [5], [6], [7], [8], [9], [10], colorectal cancer (CRC), which affects the colon and rectum [11], stands third in terms of tumour incidence, a third most diagnosed carcinogen in males, the second in females, the second cause of cancer-related deaths globally. Global Cancer Observatory (GLOBOCAN) reported that 1.15 million new cases of CRC cancer were registered worldwide in 2020. With further growth, these figures are expected to climb to 3.2 million by 2040 [10]. IARC reports that males are more likely than females to get colorectal cancer (CRC), with an estimated lifetime threat of 1 in 21 males versus 1 in 24 females in the world population [12]. Depending on people's diet, cooking methods, and lifestyle, CRC might impact individuals. Keeping a nutritious diet and engaging in regular physical activity might avoid about 50% of CRC instances.

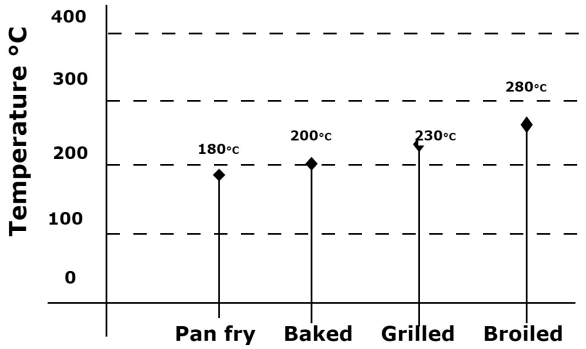


FIGURE 1. Temperature odds for various cooking methods.

Nowadays, practically everyone has the opportunity to taste various foods. Individuals prefer meat in their daily diets due to its high content of essential proteins, vitamins, and minerals. Iron (Fe) and vitamins A and B are rich in meats [13]. Though there are many different kinds of meat, the most often consumed forms are red (beef, mutton, pork, and veal), white (poultry and fish), and processed meat (pork, hamburger, and hot dogs). Consumption of red and processed meats has been connected to an increased risk of different carcinomas [14], [15], [16], [17], including a 21% increase in colon cancer threat, an 18% increased likelihood of colorectal cancer, and a 22% increase in rectal cancer incidence. The Maillard reaction occurs when red and processed meat is cooked at high temperatures such as frying, roasting, and boiling or in the oven. Due to this reaction in processed and red meat products, there is production of heterocyclic amines (HCA) [18], [19], [20], a dangerous chemical substance for humans that can cause fatal diseases like cancer [21], [22], [23], [24]. Cooked foods, especially well-done meats, contain mutagenic HCA. HCA's are the byproducts of high-temperature interactions between amino acids and creatine [25], [26]. Foods cooked at higher temperatures tend to have a bit more HCA content because the cooking temperature determines the effect of HCA on the food. Conversely, cooking the same food at a lower temperature results in lower HCA levels. This impact is more apparent in meat than fish [23]. Moreover, a possible positive link was identified between meat type, cooking method, and HCA formation in meats cooked at higher temperatures [27].

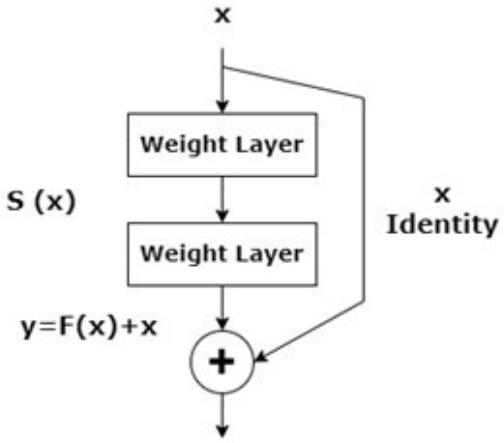


FIGURE 2. Shortcut (skip) connection.

The way red meat and processed meat are cooked, or the accumulation of carcinogens during the cooking process, may induce the formation of nitrosamines and thereby increase the risk of CRC, but the root causes remain uncertain. Cooking temperatures and time of cooking, together with the type of meat used, all determine the quantity and kinds of carcinogenic mutagens that accumulate in cooked meats [28]. Overall, it has been confirmed that cooking food by grilling, pan-frying, or barbecuing produces more mutations [29], and in particular, cooking food in pan-frying enhances producing more mutagenic activity than grilling at the same temperature [30]. As such, while assessing the risk factor for colorectal cancer, this study prioritizes how meat is cooked. (Fig.1) shows the various temperature ranges used in different cooking processes.

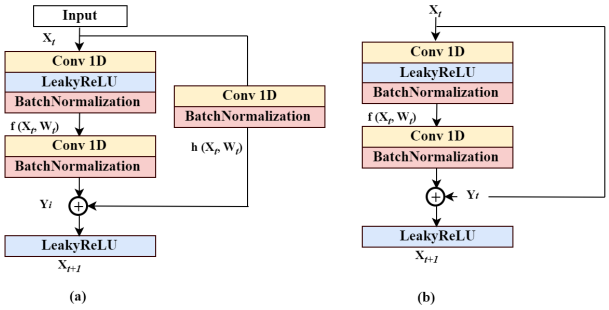


FIGURE 3. Architecture of ResNet with residual units: (a) Residual unit-based convolutional mapping, and (b) Residual unit-based identity mapping.

With the advancement of science, colorectal cancer detection might be automated using Artificial Intelligence (AI), leading to a more precise diagnosis at lower costs and in less time. Machine learning (ML) and Deep learning (DL) approaches are commonly used methods in AI-based diagnostic methods [2], [31]. Deep learning functions similarly

to unsupervised feature learning [32], [33]. DL architectures with several nonlinear layers of artificial neural networks (ANNs) extract input data without human intervention, and growing levels of abstraction can be used to find hierarchical data descriptions [34]. ResNet18 offers a novel solution to the vanishing gradient problem known as skip connections, making it the most effective technique for this study. CRC is predicted using the ResNet18 learning model, which separates the entire dataset into smaller blocks for easier processing and analyses the CRC data using various cooking methods as parameters.

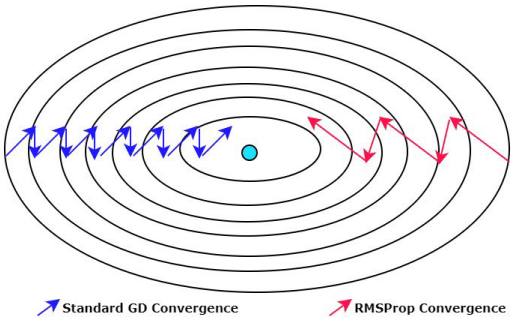


FIGURE 4. RMSProp convergence.

II. BACKGROUND

A. RESIDUAL NETWORKS (RESNET 18) DEEP LEARNING ARCHITECTURE

Deep learning models typically have layer restrictions and need time to train. Deep layers in the network have gradient vanishing concerns, which decrease performance. To address this, He et al. [35] developed the ResNet model. It addresses the gradient vanishing problem in deep convolutional neural networks (DCNNs) by placing shortcuts (residuals) between conventional layers. This is achieved by utilizing skip connections (Fig.2), allowing direct connections between layers. These skip connections enable the gradient to flow more easily during training, improving the overall training efficiency and network performance. ResNet considerably improves speed in this way, even when dealing with multiple network layers. It uses residual connections to accelerate the convergence of these complex layer architectures. Each ResNet block has stacked convolutional layers that use the previous layer's output. A related identity mapping path enhances learning by mixing the outcome of each residual block with its input [36], [37]. Additionally, using residual blocks helps to mitigate the vanishing gradient problem, which is prevalent in deep neural networks.

$$F(x) = S(x) - x. \tag{1}$$

The above (1) describes the residual function of an individual subnetwork within a multi-layer neural network. S(x) denotes a smaller subnetwork function; x is the subnetwork's input. The function F(x) computes the difference between the output of the smaller neural network S(x) and the input x. The additional information that the subnetwork discovers from the original input is stored in this function.

$$y = F(x) + x. \tag{2}$$

Equation (2) shows the computation of the subnetwork output y by adding the residual function F(x) output to the input x to integrate the residual function into the network. This strategy ensures that the network retains both the original input and the additional residual information obtained by the subnetwork.

$$y_{t+1} = F(x_t) + x_{t+1}. \tag{3}$$

Equation (3), like (2), calculates the output of the first subnetwork at time step t+1 (y_{t+1}) during the backpropagation process using the residual function $F(x_t)$ computed at time t and input x_t.

$$y = F(x_{t+1}) + x_t. \tag{4}$$

Equation (4) portrays the updated output y of the first subnetwork at time step t during the backpropagation process. The output is calculated by applying to the previous input x_t the updated residual function $F(x_{t+1})$ (computed using the input x_{t+1}). The action of '+ x' in y=F(x)+x is approached by a skip connection that executes identity mapping and links the input of a residual block to its output [38]. Fig.3 illustrates the architectural structure of the ResNet model, which uses residual blocks made up of stacked convolutional layers that use the previous layer's output. These blocks additionally have an identity mapping path, which improves learning by merging each block's output with its input.

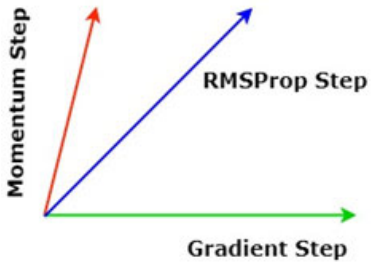


FIGURE 5. The effect of RMSProp step.

B. ROOT MEAN SQUARE PROPAGATION OPTIMIZATION ALGORITHM (RMSPROP)

Geoffrey Hinton developed RMSProp in 2012 as an adaptive optimization approach specifically for training neural networks [39], solving problems in techniques such as stochastic gradient descent (SGD). Unlike traditional methods that use predetermined learning rates, RMSProp dynamically modifies learning rates for each parameter at every time [40], [41]. This correction requires dividing the learning rate by an exponentially decaying average (EDA) of squared gradients, which helps prevent diminishing or oscillating learning rates throughout training. RMSProp ensures a more steady update direction by taking an exponentially weighted average of the gradients, decreasing oscillations, and ensuring significant

steps in the horizontal direction, thus assisting in faster optimization convergence (Fig.4). RMSProp, compared to gradient descent, changes how gradients accumulate, prioritizing recent gradient information while neglecting past histories, thereby boosting deep learning model convergence efficiency [41], [42], [43]. Notably, a huge oscillation is observed in both horizontal and vertical directions of standard GD convergence (Fig.4).

$$\vartheta_t = \beta\vartheta_t + (1-\beta)(\nabla\theta_t)^2 \tag{5}$$

$$\theta_{t+1} = \theta_t \frac{\eta}{\sqrt{sd_w}}(\theta_t) \tag{6}$$

RMSProp adjusts the learning rate to be faster in the horizontal direction while reducing oscillations in the vertical direction (Fig.5). To regulate the learning rate, RMSProp uses a moving average of the squared gradients, which normalizes the gradient updates and ensures a stable learning process. The above (5) and (6) show the computation of the gradients in the RMSprop.

Where ϑ is the exponentially decaying average of squared gradients at the time unit t. $\nabla\theta_t$ is the gradient of the loss function concerning the parameter θ at time unit t. β is the decay rate (usually set to 0.9). The learning rate is η. Equation (6) illustrates the subsequent parameter update process based on this calculation.

$$\vartheta d_w = \beta(\vartheta d_w) + (1-\beta)d_w^2 \tag{7}$$

$$\vartheta d_b = \beta(\vartheta d_b) + (1-\beta)d_b^2 \tag{8}$$

RMSProp minimizes the learning rate horizontally at each time step during training, determining the current minibatch dw & db using (7) and (8).

Equations (9) and (10) represent the update process for parameters 'w' and 'b' respectively, adapting the learning rate in accordance with dw and db values.

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\vartheta d_w}}(d_w) \tag{9}$$

$$b_{t+1} = b_t - \frac{\eta}{\sqrt{\vartheta b_w}}(b_w) \tag{10}$$

A tiny positive integer (σ, typically 10^{-7}) is added to the denominators of (9) and (10) to prevent inconsistent weight updates caused by very small ϑdw and ϑdb values. This will result in (11) and (12).

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\vartheta d_w + \sigma}}(d_w) \tag{11}$$

$$b_{t+1} = b_t - \frac{\eta}{\sqrt{\vartheta b_w + \sigma}}(b_w) \tag{12}$$

C. PERFORMANCE EVALUATION METRICS

Various metrics are applied to measure classifier performance and determine their predictive power. Accuracy is a key measurement determined as the ratio of accurately identified occurrences (true positives and negatives) to the overall cases shown in (13). The true positive rate (TPR) is the percentage of actual positive cases accurately predicted. The ratio of precisely predicted negative samples is determined by the true negative rate (TNR). Both were shown in (14) and (15).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{13}$$

$$Sensitivity(or)Recall(TPR) = \frac{TP}{TP+FN} \tag{14}$$

$$Specificity(TNR) = \frac{TN}{TN+FP} \tag{15}$$

$$F_1Score = 2 * \frac{(precision * recall)}{(precision + recall)} \tag{16}$$

The F1-score, the harmonic average of accuracy and recall, is a balanced metric that considers both false positives and false negatives, as illustrated in (16). It is a reliable statistical performance evaluation metric, especially when the class distribution is unbalanced.

Researchers commonly rely on accuracy for algorithm assessment. When a dataset is imbalanced (instances of one class are much bigger than in another), accuracy cannot be regarded as a credible metric since it is skewed toward the majority class and produces an unrealistically optimistic result [44]. In such cases, the Matthews correlation coefficient (MCC) in combination with accuracy is recommended. MCC serves as a robust alternative, initially developed by Matthews in 1975 [45] and further refined by Baldi and colleagues in 2000 [46]. The MCC was derived from the confusion matrix and calculated using the values of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) shown in (17) to measure the reliability of binary classifications.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TN+FP) \star (TN+FN) \star (TP+FP) \star (TP+FN)}} \tag{17}$$

(Lowest prediction value is -1; Highest prediction value is $+1$).

Since MCC is class symmetric, the outcome remains the same whether the positives and negatives are switched. MCC can be undefined if either of the numbers TN+FP, TN+FN, TP+FN, or TP+FP equals 0. The classifier's performance is represented by a single number falling within the range of -1 to 1. The MCC value is -1, which indicates complete disagreement (i.e., the classifier predicts every positive as a negative and every negative as a positive). The MCC value is one, indicating complete agreement, when the value is zero or near zero, meaning random guessing [47], [48].

Area Under the Receiver Operating Characteristic (AUROC) curves have become prominent in assessing the performance of machine learning and clinical diagnostic classifiers. AUROC ranges from 0 to 1. The AUROC score 1 implies perfect classification, whereas 0 shows complete misclassification. A score between 0.5-1 indicates successful positive/negative class separation, whereas a score

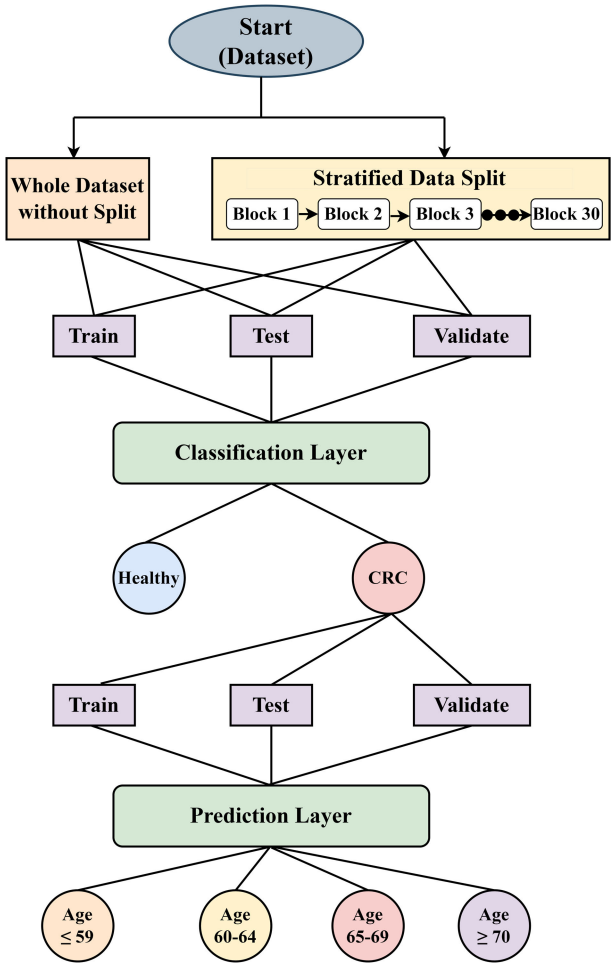


FIGURE 6. Proposed work flow for CRC detection.

of 0.5 indicates random predictions with no class-separating capacities [49].

D. RESEARCH CONTEXT AND RELATED WORK

Meat and fish diets are excellent sources of essential nutrients, including vitamins A and B, as well as minerals [13]. Red meats, in particular, are an incredible protein resource, making them a frequently consumed food in our daily diet. However, heating high-protein foods at high temperatures might result in the formation of hazardous mutagens, such as heterocyclic amines (HCAs) and polycyclic aromatic hydrocarbons (PAHs) [18]. Additionally, cooking procedures such as grilling, frying, and roasting have been shown to significantly increase the formation of these mutagens.

In 2020, Mehta et al. [50] performed a study using a US dataset to explore the association between red and processed meat intake, different cooking techniques (such as grilling, barbecuing, pan-frying, and oven-broiling), and CRC risk. The research indicated that high consumption of barbecued or grilled red meat items was related to an elevated risk of CRC in women. Similarly, Mosley et al. 2020 [51] investigated the relationship between red and processed meats, various cooking techniques (including oven-roasting, baking, grilling, barbecuing, pan-frying, and deep-frying), and CRC risk. Their results observed that these cooking techniques greatly enhanced the formation of sessile serrated lesions (SSL), consequently doubling the risk of CRC. Additionally, in the same year, Tao et al. [52] conducted research in Vietnam, concentrating on beef, various cooking techniques (such as pan-roasting, roasting, and grilling), and CRC incidence. Their investigation revealed that ingesting beef cooked using these methods increased CRC formation. Furthermore, Nassab et al. [53] conducted an investigation using an Iranian dataset and discovered that consuming high amounts of fried and grilled foods significantly raises the risk of colorectal cancer.

In 2018, de Badlay et al. [54] examined the association between meat consumption, cooking practices, and CRC risk factors. Study results showed that excessive grilled or barbecue meat consumption was correlated with a higher risk of CRC. Similarly, Lu F. et al. conducted a study in 2017 [55] that examined the relationship between HCA intake from charcoal-grilled chicken and hamburgers and the incidence of CRC. Research outcomes found a direct link between consuming high levels of HCAs from charcoal-grilled chicken and hamburgers and an increased CRC risk. Research conducted by Amit et al. in 2015 [30] proved that consuming pan-fried beef and oven-cooked ribs dramatically raised the risk of CRC. Surprisingly, consuming grilled hamburgers was observed to have a protective effect against CRC. Furthermore, studies undertaken in 2014 by Steck et al. [56] determined that red meat, especially well-done and fried red meat, was linked to a higher CRC risk.

Most prior studies have focused on specific foods or cooking methods and indicated that CRC risk increased with fried red meat, roasted beef, grilled poultry, grilled hamburgers, and barbecued meats. However, they do not recommend safe consumption levels of these foods. Our research aims to address this gap by examining a variety of foods, such as pork, beef, chicken, hamburgers, pork chops, sausages, and beef steaks, along with different cooking methods, including pan-frying, broiling, grilling, and baking. The present study analyzed and detailed the effects of these foods and cooking methods on CRC risk. Additionally, this research provides recommended quantities of certain foods prepared using specific cooking methods. This insight will ensure that individuals choose those foods and eat them in safe amounts. Rather than avoiding any foods from the regular diet, eating them in moderation can help protect against CRC incidence.

III. MATERIALS AND METHODS

A. STUDY PARTICIPANTS AND DESIGN

The PLCO Cancer Screening investigation is a large-scale, multicenter, randomized research intended to determine the impact of screening on prostate, lung, colon, and ovarian (PLCO) cancer mortality and if screening can lower the risk of death from these carcinomas [57]. Between 1993 and 2001, 1,54,892 participants (76,679 males and 78,213 females) aged 55 to 74 were recruited at ten sites throughout the

TABLE 1. Data separated into train, test, and validation using stratified shuffle.

Layers	Methods	Class	Total Sample Count	Count of Training Examples	Count of Validation Samples	Count of Test Samples
Classification	Method 1	Healthy	1,16,071	81,250	17,050	17,051
		CRC	1,815	1,270	273	272
	Method 2 (Total of 30 Blocks)	Healthy + CRC	5,684	3,978	853	853
Prediction	Age	CRC	0	0	0	0
	≤ 59		351	246	52	53
	60-64		453	317	68	68
	65-69		1,011	707	152	152
	≥ 70					

United States and randomly assigned to participate in the intervention or control arm. While individuals in the control group receive regular medical care, those in the intervention group receive screening tests [58], [59]. Prior PLCO cancer history, involvement in other cancer studies, or continuing cancer therapy were all excluded. Participants answered a self-administered questionnaire as a baseline, where demographic, dietary, and medical history information was obtained. The study was authorized by the National Cancer Institute's (NCI) human subjects review board. All ten screening centers approved the trial, and all participants provided written informed consent.

B. DATA COLLECTION

The PLCO study obtained baseline information via a self-administered baseline questionnaire (BQX) and a Dietary History Questionnaire (DHQ). The BQX gathered demographic details from 96.8% of subjects across both intervention and control arms. The DHQ was completed by 77% of participants, and dietary information was collected from both groups.

C. OUTCOME ASCERTAINMENT

Participants' CRC cases were confirmed by their pathology data, medical data, and/or death certificate information. Furthermore, individuals were also requested to disclose if they were recently confirmed to have cancer, the year and date of diagnosis, the type of cancer, and their physician's contact information.

D. DATA ACCESSIBILITY

The data mentioned in this paper were obtained from the PLCO Cancer Screening Trial. Researchers interested in accessing the data mentioned in the study should apply via the PLCO Cancer Data Access System (CDAS). Website (https://cdas.cancer.gov/learn/plco/instructions/?subtype=Data-Only).

TABLE 2. Details of the classification layer and prediction layer and deployed techniques.

	Techniques	Specifications
Classification	Batch Normalization	relu
	Dense	2 units and SoftMax activation_function
	Training Layer	loop=30, total_epochs=5, batch_size=16, Stratified data split: Training (70%), Testing (15%), Validation (15%). RMSprop (learning rate = 0.00000001),
	Employed Optimizer	Sparse categorical cross-entropy loss function, Performance metrics = MCC, AUROC
	Parameters Count	5,343,622
	Trainable Parameters Count	5,331,204
Prediction	Batch Normalization	relu
	Dense	3 units and SoftMax activation_function
	Training Layer	total_epochs=50, batch_size=16, Data split: Training (70%), Testing (15%), Validation (15%). Adam (learning rate = 0.00001),
	Employed Optimizer	loss = Sparse categorical cross-entropy loss function, Performance metrics = Accuracy
	Parameters Count	5,345,159
	Trainable Parameters Count	5,332,741

E. STATISTICAL ANALYSIS

To estimate risk ratios (RRs) with 95% confidence intervals (CIs) for relationships between meat intake or cooking style and CRC risk, a modified ResNet18 convolutional 1D model with age functioning as a time scale was employed. Participants' admission time was their present age at the beginning of the trial, and their exit time was their age at the time of cancer diagnosis, death, or the end of the follow-up, whichever came first. Participants' cancer diagnosis and demise information was updated in 2009 and 2018. To analyze CRC risk concerning meat consumption, the study chose equally spaced categories of dietary intake values: 100g increments for all food items, except for the lowest category (<100g).

The dietary intake values of the subjects are divided into consumption values for bacon, meat, chicken, hamburger, pork chops, sausage, and beef steak. For analytical purposes, food consumption values are broken down into red and white meat cooked at high and low temperatures. Dietary ingest data for the subjects were converted into grams and utilized. Following that, in the result analysis phase, we compared the participants' daily food intake values (cooked using various cooking methods) with the incidence of colorectal cancer. The study results are presented based on the entire study population and according to daily intake of red and processed meats prepared in different cooking methods in varying amounts.

Relative risk or risk ratio is a ratio that estimates the chance of an event occurring in an exposed group over the probability

TABLE 3. Performance metrics and time taken for the classification and prediction phase.

Classification Phase					
	Iteration	Epocs	MCC (-1:1)	AUROC (0-1)	Time (hh:mm:ss)
ResNet18 (Conv 1D) – Method 1	1	1	-0.60	0.20	02:18:02
	2	1	-0.87	0.34	02:52:28
	3	1	0.19	0.48	02:32:00
	4	1	0.33	0.41	03:18:48
	5	1	0.27	0.49	02:58:32
ResNet18 (Conv 1D) Method 2 Batch-Wise Training 30 Batch; 1 Batch 5 epochs	Iteration	Epocs	MCC (-1:1)	AUROC (0-1)	Time (hh:mm:ss)
	30	150	-0.15	0.20	00:47:08
	30	150	0.37	0.34	01:13:20
	30	150	0.53	0.40	00:58:52
	30	150	0.72	0.68	01:08:02
	30	150	0.80	0.85	00:50:22
Prediction Phase					
	Iteration	Epocs	MCC	Accuracy	Time (hh:mm:ss)
ResNet 18 (Conv 1D)	1	50	0.57	93.4 %	00:18:56
	2	50	0.74	95.8 %	00:14:08
	3	50	0.77	96 %	00:13:21
	4	50	0.85	96.4 %	00:20:50
	5	50	0.88	97 %	00:16:02

TABLE 4. Baseline characteristics and colorectal cancer.

Attributes			RR	95% CI
Age	Non-Veg	≤ 59	0.48	0.42-0.54
		60-64	0.95	0.86-1.05
		65-69	1.46	1.32-1.61
		≥ 70	1.58	1.41-1.78
Occupation	Homemaker		0.92	0.79-1.07
	Working		0.78	0.70-0.86
	Unemployed		1.13	0.73-1.75
	Retired		1.31	1.19-1.43
	Extended Sick Leave		0.31	0.04-2.23
	Disabled		0.87	0.62-1.23
	Other		1.14	0.84-1.55
Smoking	Never		0.86	0.78-0.94
	Current		1.14	0.99-1.31
	Former		1.11	1.01-1.22
Drinking	Never		0.97	0.81-1.16
	Former		1.05	0.90-1.21
	Current		1.26	1.06-1.88
CRC Cancer History	No		0.39	0.35-0.43
	Yes		2.57	2.30-2.87
Family Cancer History	No		0.77	0.67-0.88
	Yes		1.3	1.13-1.50

of an event occurring in an unexposed group [60].

$$RiskRatio = POe/POu \tag{18}$$

Equation (18) POe represents the likelihood of an event occurring in the exposed class, while POu represents the chance of an event occurring in the unexposed class. RR > 1: The event is more likely to occur. RR < 1: The event is less likely to occur. RR of 1: No difference in the event.

IV. IMPLEMENTATION OF THE PROPOSED RESNET18 (CONV 1D)

The study utilizes a large dataset of around 1,54,892 participants (76,679 males and 78,213 females) records, which provides precise information on how people consume meat and covers a wide range of meat consumption habits. This comprehensive analysis enabled us to investigate the complex relationship between various eating patterns and colorectal cancer. Nonetheless, due to a shortage of positive instances in the dataset, examining the relation between meat-derived mutagens and CRC risk caused challenges during analysis.

The proposed procedure for implementing colorectal cancer detection using a modified ResNet18 (Conv 1D) workflow structure is shown in (Fig. 6). The dataset initially had a lot of noise; therefore, duplicate features were removed to speed up the training process to retain the accuracy. This consisted of two significant steps: Data cleansing involved replacing erroneous values in demographic and dietary information with appropriate ones and ensuring uniform data types within columns for better integration with the proposed ResNet model. Furthermore, feature reduction entailed optimizing the dataset by removing blank, zero, and negative entries, especially in dietary profiles frequently filled out as alphanumeric values. After successfully eliminating the above data, only 1,17,886 (1,16,071- Healthy and 1,815-Cancer) objects were left for the following consecutive process.

One fully coupled neural network layer and block normalization are employed independently in the classification and prediction layers (Fig. 7). The trained classifier layers, with uniquely assigned class weights, are then used to categorize features into healthy or colorectal cancer (CRC) classes. Following categorization, the groups of colorectal cancer patients were forwarded to the prediction phase. In the prediction phase, trained prediction layers with uniquely assigned class weights are employed to estimate the age range of CRC patients. A customized ResNet18 (conv 1D) structure is used for the classification method (1 and 2) and the prediction method. Table 2 contains information like the number of training epochs, size of the batches, optimizers, and learning rate utilized during classification and prediction layer training. Table 2 also explains how the number of trainable parameters in the learning model varies depending on this study's ResNet18 (conv 1D) model.

A. EXPERIMENTAL SETUP

Upon eliminating noise, the normalized and refined data undergo a series of transformations as a crucial preprocessing step before being given into the learning model. Subsequently, out of the total pool of 1,54,892 individuals, approximately 1,16,071 individuals in healthy, and 1,815 with cancer objects were identified for further analysis. Two unique methods were used in the context of learning models. In the first method, the preprocessed dataset is fed straight into the learning model; in the second method, the refined dataset is divided into thirty smaller, block-sized data

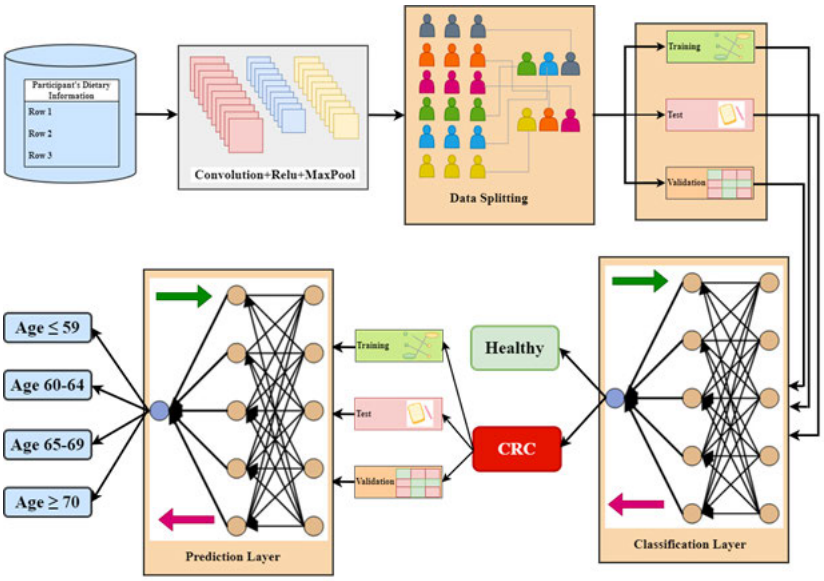


FIGURE 7. Overview of the proposed approach for CRC detection using ResNet18 (Conv 1D) model.

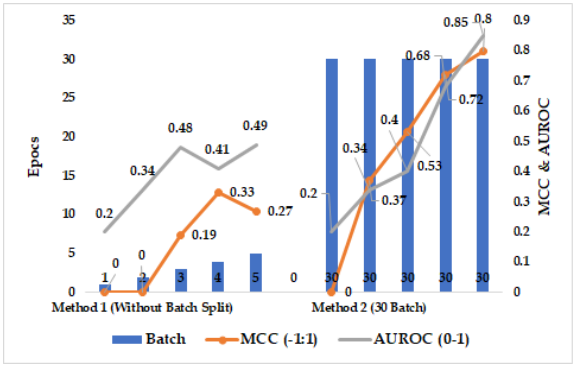
for in-depth analysis. Notably, participants' demographic information was withheld from the dataset in line with the research objective, and only dietary information was provided for both approaches. Furthermore, the healthy and cancer participants were split equally in each batch. Thus, approximately 3,869 participants for each block were evenly distributed and arranged into 30 blocks from a total population of 1,16,071 healthy participants. In contrast, all 1,815 cancer participants were included in 30 blocks. So, each batch comprised 5,684 individuals, resulting in 30 batches encompassing approximately 1,17,000 healthy individuals and 1,815 cancer patients. The colo-exit-days were used to find when individuals left the trial and to determine the age range in which participants were most likely to develop cancer. We observed a wide range of colo-exit-days in the study, from a minimum of one day to a maximum of 5,906 days.

B. CLASSIFICATION PHASE

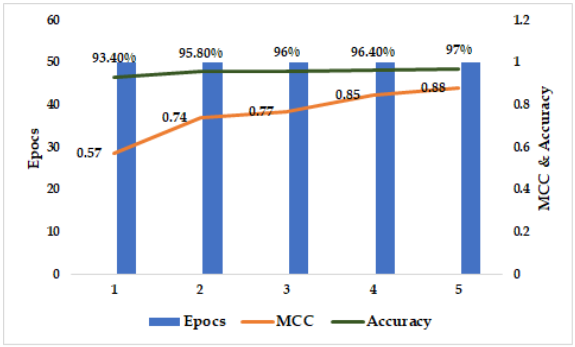
The proposed ResNet18 (Conv1D) model is well-suited for real-time sequential data. This research utilizes the ResNet18 (Conv1D) CNN architecture to extract features, classify healthy and cancer data, and predict the age of cancer patients. After filtering out irrelevant information, a modified dataset containing the dietary information of the participants (both healthy and cancer patients) is created and sent for further analysis. Using a stratified shuffle split technique, the dataset is divided into training, validation, and test sets in a 70:15:15 ratio. The validation set helps prevent overfitting and enhances the model's performance on new, unseen data. Each time, stratified shuffle split randomly picks the samples based on the original dataset's class ratio. Stratified shuffle split ensures that the class balance in the resulting sets reflects the original dataset's class distribution, as shown in Table 1. The typical ResNet18 convolutional 2D model is customized into a convolutional 1D model using appropriate residual blocks, batch normalization, and activation functions, making it suitable for the real-time sequential task of colorectal cancer classification. A custom callback function is then used to evaluate the model's performance during training. The loop function executes the training process 30 times (epochs), processing cancer and healthy data into training, validation, and test sets in each iteration. It initializes and loads the ResNet18 (Conv1D) model, compiles it with a specified loss function and optimizer, and trains it with specified class weights to address the class imbalance. The class weights are set at 0.7344 for healthy patients and 1.5661 for cancer patients, ensuring balanced distribution during training. During training, callbacks are used to save the model's performance metrics at each epoch.

C. PREDICTION PHASE

This phase uses the prediction layer to predict the age of patients diagnosed with colorectal cancer. Based on a cohort of 1,815 identified CRC cases, the study revealed a noteworthy finding: a total absence of CRC diagnoses in the age range of 51 years or younger. Subsequently, the remaining patients were stratified into three distinctive age groups for further analysis: individuals aged 50-64 years ($n = 351$), 65-69 years ($n = 453$), and 70 years ($n = 1,011$). To account for participant exit due to CRC detection or mortality, we employed the colo-exit-age variable, which records each participant's age of exit, providing valuable data for analyzing potential relationships between age and CRC outcomes within our research.



(a)



(b)

FIGURE 8. a) Comparison of MCC and AUROC in classification with and without batch split for ResNet 18 (Conv 1D) Model. b) Comparison of Prediction Phase MCC and accuracy for ResNet 18 (Conv 1D).

Before model training, we addressed the class imbalance in the distribution of identified CRC cases. We employed the "balanced" variable to calculate specific class weights inversely proportional to the class frequencies in the target variable (y). These class weights were incorporated during the training to handle the potential class imbalance and enhance model performance (class weights: 50-64 years = 1.7236, 65-69 years = 1.3355, 70 years = 0.5984). To maintain class distribution within the training, validation, and test sets, a stratified shuffle-split technique separates the data at a 70:15:15 ratio. Subsequently, the proposed custom ResNet18 (Conv1D) model was constructed utilizing residual blocks, batch normalization, and activation functions. Then, the ResNet18 (Conv1D) model was pre-loaded for training, with an internal looping structure to ensure training for 50 epochs.

V. RESULTS

At first, we evaluated the learning model by categorizing the whole dataset directly without using block splitting. The dataset was then segmented into thirty blocks, and the classification phase was used to test each of the distinct blocks. Both methods used the same classification layer parameters. The acquired MCC and AUROC values during the classification phase of CRC prediction are shown in Fig 9, whereas Fig 10 illustrates the confusion matrix produced

TABLE 5. Meat consumption and colorectal cancer risk.

Meat variables	g/d	Cases	RR	95% CI
Meat Prepared using	0-25	1772	0.89	0.66-1.21
High - Temperature	26-50	41	1.2	0.88-1.63
Cooking Techniques	≥51	1	0.30	0.04-2.14
Meat Prepared using	0-25	1215	0.94	0.85-1.03
Low - Temperature	26-50	480	1.08	0.97-1.19
Cooking Techniques	≥51	108	1.2	0.99-1.21
Red Meat Prepared using	0-25	1184	0.9	0.82-1.00
High Temperature	26-50	371	1.06	0.94-1.18
Cooking Methods	≥51	214	1.14	0.99-1.32
Red Meat Prepared using	0-25	798	1	0.91-1.10
Low Temperature	26-50	536	1.24	1.12-1.37
Cooking Methods	≥51	423	1.32	1.92-2.14
White Meat (Excluding	0-25	640	0.94	0.85-1.04
Chicken Pan-Frying,	26-50	525	1	0.90-1.10
Grilling, or Barbecuing)	≥51	593	1.07	0.97-1.18
White Meat (Excluding	0-25	745	0.94	0.86-1.03
Chicken Pan-Frying,	26-50	517	1.03	0.93-1.14
Grilling, or Barbecuing, Baked, and Broiled)	≥51	504	1.05	0.94-1.16
Processed Meat Selection:	0-25	1224	0.88	0.79-0.97
Hamburger, Hot Dogs, and	26-50	275	1.1	0.97-1.25
Cold Cuts	≥51	244	1.13	0.99-1.29
Assorted Processed Meats:	0-25	1002	0.85	0.77-0.93
Hamburger, Bacon, Sausage,	26-50	371	1.11	1.00-1.25
Hot Dogs, and Non-Poultry Cold Cuts	≥51	356	1.13	1.01-1.27
Diverse Processed Meats:	0-25	811	0.87	0.79-0.95
Ham, Bacon, Sausage,	26-50	415	1.16	1.04-1.29
Hot Dogs, and Cold Cuts	≥51	493	1.05	0.95-1.16
	0-25	1045	0.86	0.78-0.95
Processed Red Meat	26-50	346	1.11	0.99-1.25
	≥51	332	1.13	1.00-1.27
	≤10	531	0.98	0.89-1.09
Total Poultry	11-20	366	1.03	0.92-1.15
	≥21	819	1	0.91-1.09
	≤10	1774	1.09	0.75-1.59
	11-20	18	0.94	0.59-1.49
Poultry	≥21	9	0.88	0.46-1.69
(Deep Fried & Stewed)	≤10	1800	1.23	0.73-2.08
	11-20	12	0.92	0.52-1.61
	≥21	2	0.48	0.12-1.90
	0-25	1768	0.73	0.54-1.00
Hamburger (Fast Food)	26-50	32	1.51	1.07-2.14
	≥51	7	1.94	0.45-2.96
Pork Chops	0-25	1814	1.35	0.47-2.69
(Pork Roast and	26-50	1	0.35	0.05-0.51
Mixed Pork Dishes)	≥51	-	-	-

in the age prediction phase. In Fig 10, the ages 60-64 are represented by label 0, 65-69 by label 1; and 70 and above by label 2. During the classification phase, the highest MCC and AUROC values achieved in the first approach were 0.27 and 0.49, respectively, indicating poor performance of the learning model without block-split. However, the second approach, where the data was divided into 30 blocks, achieved the highest MCC value of 0.80 and AUROC value of 0.85. On the other hand, the prediction phase yielded a maximum MCC value of 0.88 and an accuracy of 97%. Rather than providing the whole dataset all at once to the classification phase, this study discovered that sending the dataset divided into 30 blocks greatly enhanced the learning model's performance.

This research focuses on detecting CRC patient and predicting their ages. Therefore, MCC and AUROC values

Snapshots from the Classification Phase

```
Loop_Trianing_Iteration: 27
model loaded res18_v1-26.h5
Epoch 1/5
248/249 loss: 0.5356 - accuracy: 0.7543#####TEST
27/27
[[465 116]
[ 60 212]]
matthews_corrcoef 0.5553940153130643
ROAUC 0.789877999392528
Epoch 1:
249/249 loss: 0.5355 - accuracy: 0.7539 - val_loss: 0.4982 - val_accuracy: 0.7937
Epoch 2/5
249/249 loss: 0.5331 - accuracy: 0.7650#####TEST
27/27
[[465 116]
[ 60 212]]
matthews_corrcoef 0.5553940153130643
ROAUC 0.789877999392528
Epoch 2:
249/249 loss: 0.5331 - accuracy: 0.7650 - val_loss: 0.4973 - val_accuracy: 0.7937
Epoch 3/5
249/249 loss: 0.5305 - accuracy: 0.7547#####TEST
27/27
[[458 123]
[ 58 214]]
matthews_corrcoef 0.5482093536288751
ROAUC 0.7875303735952212
```

Snapshots from the Classification Phase

```
Epoch 3:
249/249 loss: 0.5305 - accuracy: 0.7547 - val_loss: 0.5006 - val_accuracy: 0.7878
Epoch 4/5
248/249 loss: 0.5323 - accuracy: 0.7538#####TEST
27/27
[[462 119]
[ 60 212]]
matthews_corrcoef 0.5495196331159672
ROAUC 0.7872962437987243

Epoch 4:
249/249 loss: 0.5316 - accuracy: 0.7541 - val_loss: 0.4968 - val_accuracy: 0.7902
Epoch 5/5
249/249 loss: 0.5393 - accuracy: 0.7491#####TEST
27/27
[[468 113]
[ 61 211]]
matthews_corrcoef 0.5581230285358333
ROAUC 0.7906215196922143

Epoch 5:
249/249 loss: 0.5393 - accuracy: 0.7491 - val_loss: 0.4936 - val_accuracy: 0.7960
```

FIGURE 9. MCC and AUROC snapshots from the ResNet18 (conv 1D) classification phase.

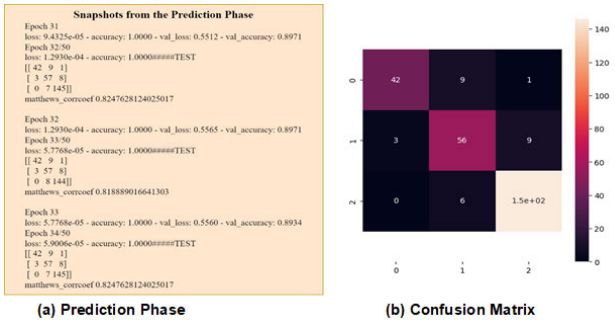


FIGURE 10. Snapshots and confusion matrix from the prediction phase.

of the classification phase (both approaches) are related to the correct identification of the CRC classes. Similarly, the accuracy value is associated with the accurate prediction of the CRC patient's age prediction phase. The findings demonstrate that models without block split have lower MCC and AUROC values in comparison to the suggested block-splitting model. High accuracy and MCC values are also shown in the prediction phase, which proves that the models are good at predicting the ages of CRC patients. These results show how the suggested models can accurately estimate the age of CRC patients and how important block splitting is for better classification results.

We also summarize the demographic, lifestyle, familial cancer, and CRC cancer features found in this cohort analysis and unveils key risk factors associated with CRC. Individuals aged 65-69 years and those over 70 had notably higher CRC risks (RR: 1.46, CI: 1.32-1.61) and (RR: 1.58, CI: 1.42-1.78), respectively. Retirement and unemployment emerged as significant factors, showing elevated CRC likelihood among retirees (RR: 1.31, CI: 1.19-1.43) and jobless individuals (RR: 1.13, CI: 0.73-1.75). Both current and former smokers confronted increased CRC threats (RR: 1.14, CI: 0.99-1.31) and (RR: 1.11, CI: 1.01-1.22), respectively. Likewise, alcohol consumption, whether present or past, showed a positive link with CRC threat (RR: 1.26, CI: 1.06-1.88) and (RR: 1.05, CI: 0.90-1.21). The presence of a cancer history among

TABLE 6. Broiled, Grilled, and Baked meat intake and colorectal cancer.

Food Items	g/d	Cases	RR	95% CI
Broiled				
Meat	≤10	1604	0.79	0.68-0.92
	11-20	120	1.25	1.04-1.50
	≥21	66	1.25	0.98-1.60
Poultry	≤10	1770	0.77	0.57-1.06
	11-20	32	0.79	0.60-1.11
	≥21	7	0.8	0.78-1.67
Hamburger	0-25	1815	1.55	0.22-2.89
	26-50	-	-	-
	≥51	-	-	-
Pork Chops	0-25	1815	1.94	0.28-3.67
	26-50	-	-	-
	≥51	-	-	-
Beef Steak	0-25	1794	0.68	0.45-1.05
	26-50	20	1.46	0.96-2.24
	≥51	-	-	-
Grilled				
Meat	≤10	1259	0.98	0.88-1.09
	11-20	258	0.97	0.85-1.11
	≥21	224	1.07	0.93-1.23
Poultry	≤10	1736	1.11	0.87-1.41
	11-20	51	0.93	0.71-1.23
	≥21	17	0.84	0.52-1.34
Hamburger	0-25	1795	0.68	0.44-1.07
	26-50	15	1.36	0.82-2.24
	≥51	4	2.06	0.79-3.42
Pork Chops	0-25	1813	1.55	0.64-2.14
	26-50	2	0.46	0.11-1.82
	≥51	-	-	-
Beef Steak	0-25	1764	0.99	0.75-1.30
	26-50	38	0.94	0.68-1.29
	≥51	13	1.31	0.76-2.25
Baked				
Meat	≤10	1521	1.02	0.89-1.17
	11-20	179	1.08	0.93-1.26
	≥21	69	0.79	0.62-1.00
Poultry	≤10	1658	1.2	1.00-1.44
	11-20	87	0.81	0.65-1.00
	≥21	41	0.9	0.66-1.23
Pork Chops	0-25	1809	1.38	0.62-2.06
	26-50	5	0.72	0.30-0.72
	≥51	1	0.77	0.11-0.41

the immediate family members of participants (RR: 1.3, CI: 1.13-1.50) and a prior incidence of CRC (RR: 2.57, CI: 2.30-2.87) increased the chance of developing CRC.

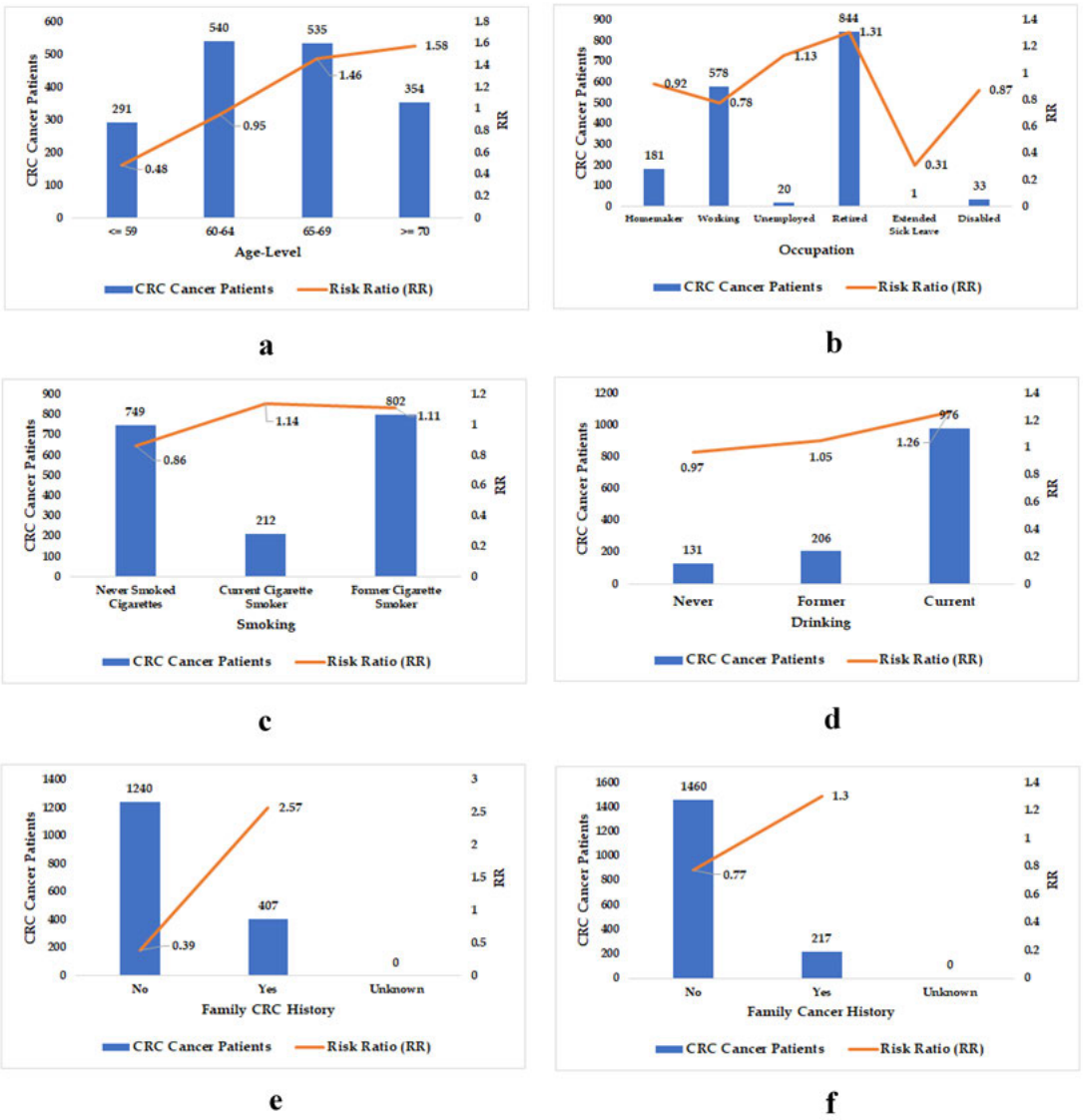


FIGURE 11. a) Comparison between CRC risk factors with cancer patients in different age groups of participants. b) Comparison between CRC risk factors with cancer patients belonging to different occupations. c) Comparison between CRC risk factors with cancer patients associated with participants' smoking habits. d) Comparison between CRC risk factors with cancer patients associated with participants' drinking habits. e) Comparison between CRC risk factors with cancer patients associated with participants' family CRC history. f) Comparison between CRC risk factors with cancer patients associated with participants' family cancer history.

These diverse risk factors provide valuable insights into comprehending and potentially mitigating CRC risks prevalent in societies. Fig 11 shows the CRC risk factor comparison of participant's general characteristics.

A. MEAT INTAKE AND CRC RISK

Every meat (red, white, processed, and processed red meat) has statistically significant favorable relationships with CRC risk, independent of cooking techniques. Excluding roasted pork chops, which showed a negative connection with CRC risk even at intake levels exceeding 26g/d (RR: 0.35, CI: 0.05-0.51), the majority of meat variables were associated with increased risk estimations. However, when all meats cooked at high temperatures are accounted for, there is no strong evidence of a relationship between meat diets and CRC risk.

Regardless of cooking temperature (high or low), red meat was linked to an increased risk of colorectal cancer (CRC), especially when consumed in excess of 26g/d (RR: 1.14, CI: 0.99-1.32; and RR: 1.32, CI: 1.92-2.14, respectively). Though no correlation was found between the overall poultry intake and CRC threat, eating in excess of 26g/d of fried or barbecued white meat was linked to an increased risk of CRC (RR: 1.07, CI: 0.97-1.18). Additionally, daily consuming more than 26g of specific processed meat types, such as processed red meat, processed ham, and hot dogs, processed

TABLE 7. Pan-fried meat consumption and colorectal cancer risk.

Food Items	g/d	Cases	RR	95% CI
Bacon	≤10	1777	0.97	0.69-1.35
	11-20	35	1.1	0.79-1.53
	≥21	-	-	-
Meat	≤10	1408	0.93	0.83-1.04
	11-20	222	0.9	1.04-1.07
	≥21	127	0.91	0.76-1.09
Poultry	≤10	1787	1.74	1.11-2.72
	11-20	18	0.8	0.51-1.27
	≥21	1	0.1	0.01-0.68
Hamburger	0-25	1801	0.62	0.36-1.06
	26-50	13	1.86	1.09-3.18
	≥51	-	-	-
Pork Chops	0-25	1810	1.12	0.47-2.69
	26-50	5	1.05	0.44-2.50
	≥51	-	-	-
Sausage	0-25	1807	0.53	0.27-1.06
	26-50	5	1.66	0.70-1.94
	≥51	3	2.4	0.79-2.29
Beef Steak	0-25	1805	1.2	0.63-2.30
	26-50	8	0.95	0.48-1.89
	≥51	1	0.43	0.06-3.01

non-poultry cold cuts, and processed bacon and sausages, exhibits a positive association with heightened CRC risk (RR: 1.13, CI: 1.00-1.27; RR: 1.1, CI: 0.97-1.25; RR: 1.13, CI: 1.01-1.27; and RR: 1.16, CI: 1.04-1.29, respectively). Interestingly, a strong positive correlation exists between increased consumption of fast-food-style hamburgers and CRC threat (RR: 1.94, CI: 0.45-2.96).

B. PAN-FRIED MEATS AND CRC RISK

The study examined the relationship between CRC risk and the consumption of various types of meat cooked using pan-frying (''a fast cooking method involving a preheated frying pan''). The meats assessed encompassed beef steak, bacon, meat, poultry, hamburger, pork chops, and sausage. Findings suggest that consuming more than 26g of fried hamburgers (RR: 1.86, CI: 1.09-3.18); and fried sausages (RR: 2.4, CI: 0.79-2.29) daily, as well as 11g of bacon consumption (RR: 1.1, CI: 0.79-1.53) raises the CRC hazards. On the other hand, a higher intake of pan-fried meat (RR: 0.91, CI: 0.76-1.09); pan-fried chicken (RR: 0.8, CI: 0.51-1.27); and pan-fried beef steak (RR: 0.43, CI: 0.06-3.01) showed a significant negative relationship with CRC. However, no noteworthy connections were observed between other types of meat and CRC risk.

C. BROILED, GRILLED, AND BAKED MEATS AND CRC RISK

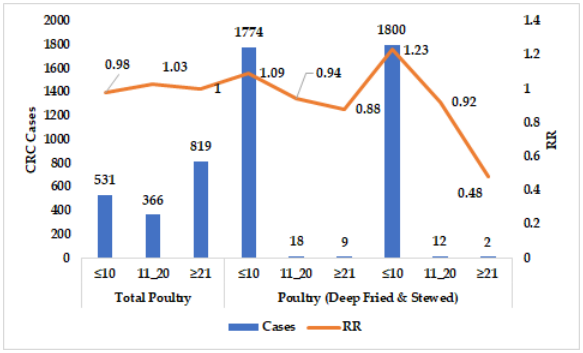
Daily broiled chicken consumption reduces (RR: 0.8, CI: 0.78-1.67) colorectal cancer risks, while broiled beef steak (RR: 1.46, CI: 0.96-2.24) and broiled meat (RR: 1.25, CI: 0.98-1.60) have statistically elevated CRC risk. Broiled hamburgers and pork chops have inconsistent risks. Moreover, a statistically significant positive link was observed between the intake of grilled or barbecued meat, hamburger, and beef steak (RR: 1.07, CI: 0.93-1.23; RR: 2.06, CI: 0.79-3.42; and RR: 1.31 CI: 0.76-2.25, respectively). Meanwhile, there was a substantial negative correlation between grilled or

FIGURE 12. a) Comparison of CRC risk factors with meat and red meat cooked in high and low temp. b) Comparison of CRC risk factors with white meat (excluding chicken pan-frying, grilling, or barbecuing). c) Comparison of CRC risk factors with various processed meats and red meats.

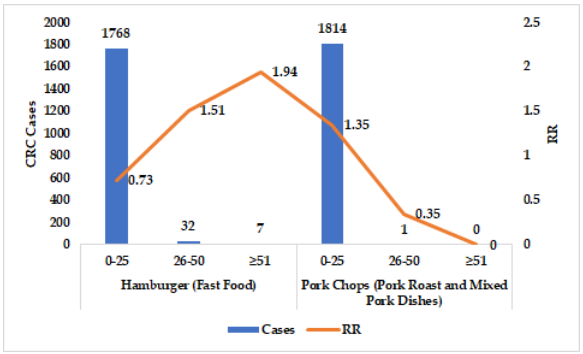
barbecued poultry (RR: 0.84, CI: 0.52-1.34) and pork chops (RR: 0.46, CI: 0.11-1.82). Concerning baked food, excessive consumption of chicken (RR: 0.79, CI: 0.62-1.00), pork chops (RR: 0.9, CI: 0.66-1.23), and beef (RR: 0.77, CI: 0.11-1.41) was statistically showed a strong negative link with CRC.

VI. DISCUSSION

Our research investigates the relationship between the risk of colorectal cancer and the intake or preparation of various types of meat, and no definitive positive link to colorectal cancer was identified with any particular meat. However, it has been observed that how meat is prepared may have

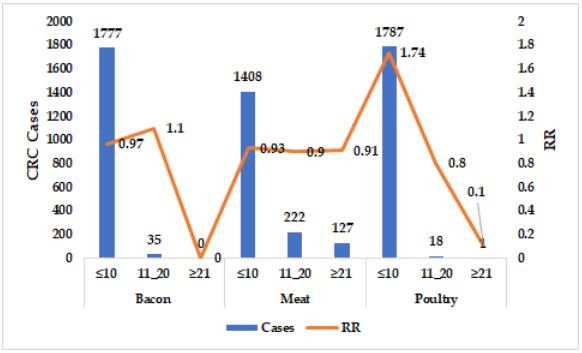


(a)

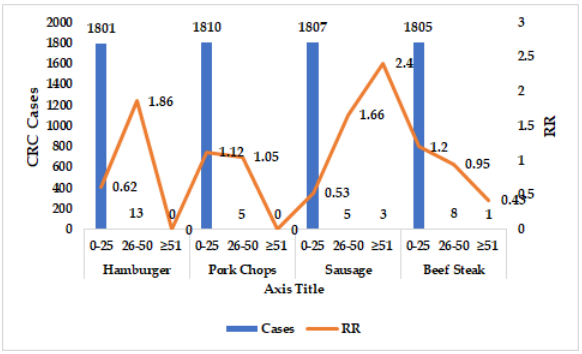


(b)

FIGURE 13. a) Comparison of CRC risk factors with Deep-fried & stewed poultry. b) Comparison of CRC risk factors with hamburger and pork chops.



(a)



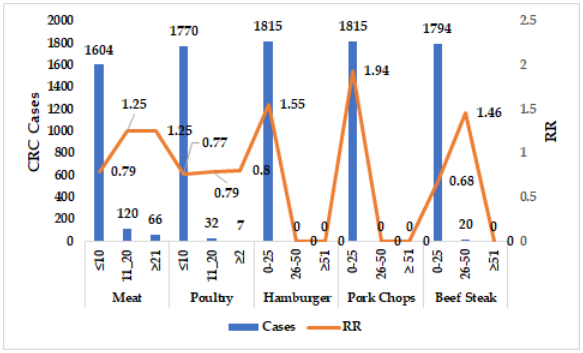
(b)

FIGURE 14. a) Comparison of CRC risk factors with pan-fried bacon, meat, and poultry. b) Comparison of CRC risk factors with Pan-fried Beef Steak, Hamburger, Pork Chops, and Sausage.

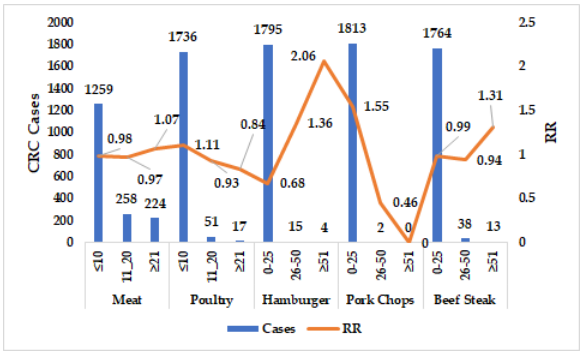
a more significant impact than the amount consumed. As a result, in this cohort research, an analysis of meat consumption behaviors with portion sizes and cooking techniques was undertaken. Processed red meat, processed ham, hot dogs, various processed cold cuts excluding chicken, as well as processed bacon and sausages, have all been linked to an increased risk of colorectal cancer. The substantial correlation usually reported between increased intake of red meat (cooked at high or low temperatures) and CRC risk may be due to the development of mutagens such as heterocyclic amines (HCAs) during the cooking process. When red meat is cooked at temperatures higher than 150°C, HCA molecules accumulate, increasing the risk of CRC. Our study confirms the findings of several cohort and case-control studies [50], [61], [62], [63], [64], [65] and demonstrates a substantial correlation between the consumption of red meat and the risk of colorectal cancer (CRC). There was no statistically significant positive correlation identified between consuming white meat and certain types of red meats like pork and an increased likelihood of colorectal cancer. However, a few studies, both cohort and case-control, have revealed no apparent association between red meat consumption and the possibility of CRC [66], [67].

Mutations that occur during high-temperature red and white meat cooking are distinct, while the process behind these disparate interactions between mutations remains unclear. Some studies suggest that the meat type and cooking temperature may decide the HCAs (heterocyclic amines) and PAHs (polycyclic aromatic hydrocarbons) compounds formed from red and white meats [28], [63]. However, compounds such as heme iron, which usually appears in red meat, may increase the risk of colorectal cancer [23]. One of the notable findings suggests that the cooking method may play a crucial role in the relationship between food types and CRC risk. Bacon, hamburger, and sausage prepared at high temperature exhibits a positive link. Meanwhile, significant inverse associations were seen in the intake of chicken and pork chops cooked by any cooking method like pan-fried, broiled, grilled, and baked, indicating a potential preventive benefit against CRC. This may be attributed to the formation of harmful compounds, such as HCAs and PAHs, during cooking. Pan-fried beef steak and meat show a negative link. Besides, both foods prepared by the broiling method exhibit a positive link. Some foods showed a statistically significant positive or negative association with CRC regardless of cooking methods. Certain food items showed variations in their effect on CRC depending on the cooking method.

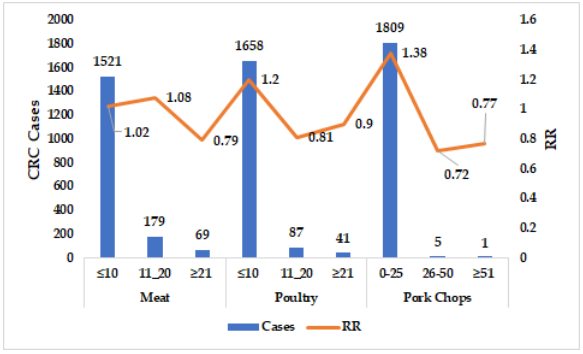
Previous studies on the relationship between meat consumption and colorectal cancer have yielded inconsistent results. This can be attributed to the different methodologies utilized in cohort, case-control, and population-based studies, as well as the wide range of variables used as exposure measures. Dietary information collected from the majority of participants in cohort studies occurred prior to their cancer



(a)



(b)



(c)

FIGURE 15. a) Comparison of CRC risk factors with Broiled Meat, Poultry, Hamburger, Pork Chops, and Beef Steak. b) Comparison of CRC risk factors with Grilled Meat, Poultry, Hamburger, Pork Chops, and Beef Steak. c) Comparison of CRC risk factors with Baked Meat, Poultry, and Pork Chops.

diagnosis. Consequently, most case-control studies [52], [54], [68], [69] have revealed a positive correlation between meat consumption and colorectal cancer compared to findings in cohort studies [70], [71]. Despite a few foods exhibiting a positive link in this study, the statistical significance of their influence on CRC was robust.

Our research has a few limitations. First, when participants were diagnosed with cancer, they were allowed to self-report the specifics of their diagnosis, and death certificates were also considered as evidence of cancer. Sometimes, the information provided in the death certificate is also likely to be erroneous. As a result, more transparency in cancer confirmation should be promoted. Future work should focus on integrating robust clinical data sources and validation processes to strengthen the accuracy and reliability of cancer diagnoses. Second, participants gave identical values to several nutritional indicators because they were given the flexibility to enter and change dietary information at different levels. Consequently, they filled in multiple dietary variables on the Food Frequency Questionnaires (FFQ) forms with the same numbers and left several columns unfilled. Many essential pieces of information are thus either absent or inaccurate. The integrity of the details supplied by the participants during the experiment was recorded without cross-validation. Therefore, strict data entry protocols and robust data validation techniques to ensure that the data obtained provide sufficient and complete information should be implemented in the future and focused on increasing data quality. This could significantly improve the accuracy of the colorectal cancer prediction. Third, because no comprehensive dietary evaluation approach was employed, the nutritional values of certain foods were limited. At the same time, the dietary contents of several foods were insufficient to be incorporated into numerous cooking methods. Therefore, this has led to a lack of clarity on the effects of certain foods and cooking methods on the CRC risk. To better understand the link between cooking methods and colorectal cancer risk, further investigation should be undertaken, combining thorough food records with detailed information about various cooking methods.

In summary, high-temperature cooking can increase the risk of colorectal cancer by causing hazardous mutagens to form in the food. Processed meat consumption, particularly ham, bacon, and sausages, has been associated with an elevated risk of CRC. These findings suggest that epidemiological research on the connection between meat intake and CRC should consider the type of meat consumed and how it is cooked. Overall, our results encourage the intake of less red and processed meat.

DECLARATIONS

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AVAILABILITY OF DATA AND MATERIAL

All data utilized or analyzed during this study are available in the NCI upon reasonable request.

AUTHORS' CONTRIBUTIONS

S. Thanga Prasath performed writing–data curation; formal analysis; investigation; methodology; original draft and conceptualization; review and editing. C. Navaneethan performed–conceptualization; supervision; and validation of the final version of the manuscript.

CONFLICTS OF INTERESTS

The authors declare no potential conflicts of interest.

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