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Role of artificial intelligence in the diagnosis and treatment of hepatocellular carcinoma

Rajesh Kumar Mokhria, Jasbir Singh

**Abstract**

Artificial intelligence (AI) evolved many years ago, but it gained much advancement in recent years for its use in the medical domain. AI with its different subsides, i.e., deep learning and machine learning, examine a large amount of data and performs an essential part in decision-making in addition to conquering the limitations related to human evaluation. Deep learning tries to imitate the functioning of the human brain. It utilizes much more data and intricate algorithms. Machine learning is AI based on automated learning. It utilizes earlier given data and uses algorithms to arrange and identify models. Globally, hepatocellular carcinoma is a major cause of illness and fatality. Although with substantial progress in the whole treatment strategy for hepatocellular carcinoma, managing it is still a major issue. AI in the area of gastroenterology, especially in hepatology, is particularly useful for various investigations of hepatocellular carcinoma because it is a commonly found tumor, and has specific radiological features that enable diagnostic procedures without the requirement of the histological study. However, interpreting and analyzing the resulting images is not always easy due to change of images throughout the disease process. Further, the prognostic process and response to the treatment process could be influenced by numerous components. Currently, AI is utilized in order to diagnose, curative and prediction goals. Future investigations are essential to prevent likely bias, which might subsequently influence the analysis of images and therefore restrict the consent and utilization of such models in medical practices. Moreover, experts are required to realize the real utility of such approaches, along with their associated potencies and constraints.

**Key Words:** Hepatocellular carcinoma; Artificial intelligence; Deep learning; Machine learning; Support vector machines; Artificial neural networks
INTRODUCTION

Hepatocellular carcinoma (HCC) is a malignancy of the liver that is very lethal. It is the most commonly found primary adult liver malignancy. Worldwide it is the third most common cause of cancer-related death[1]. According to the American Cancer Society, 42810 new liver and intrahepatic cholangiocarcinoma cases were detected in 2020, of which 30160 died[2]. Surgery (liver transplantation and resection) is the backbone of HCC treatment and is the only possible treatment option. Delamination or removal is an alternative treatment for small tumors. In addition, intra-arterial treatment and chemotherapy can control the disease to some extent[1]. In addition, HCC has certain radiological features that do not require histological examination for diagnosis. Therefore, the analysis and interpretation of diagnostic imaging procedures are not always easy as it changes during the disease course. The same applies to diagnosis/prognosis and treatment response, as they are influenced by numerous factors.

Artificial intelligence (AI) is the computer simulation of the human intelligence process. The concept of AI emerged in the 1950s[3], but only a few years ago it made real progress. It has been used in a variety of industries, i.e. image and natural language processing. In the field of medicine, AI is becoming increasingly significant. The utilization of AI is rapidly expanding and is increasingly useful in understanding gastrointestinal diseases[4-6]. The phrase “artificial intelligence” refers to a group of computer programs that attempt to mimic human brain capabilities, i.e. learning and problem-solving.

AI has evolved into a separate discipline called machine learning (ML). ML examines data to develop algorithms that can recognize distinct behavior forms and confirm predictive models. ML focuses on developing mathematical models that assist machines in making predictions or judgments without being explicitly programmed. Various ML techniques, for instance, support vector machines (SVM), artificial neural networks (ANNs), classification, and regression trees, seem to be employed in various investigations in the medical discipline[7]. Deep learning (DL) has emerged as an emerging paradigm of ML for developing multilayered neural network algorithms, and approaches like convolutional neural network (CNN), an ANN multilayer, have been widely accepted and used in radiological image analysis[8,9].

In a nutshell, ML is a core branch of AI, and DL is used to implement it. The use of ML and DL to forecast the risk of gastric cancer has been successful[10]. Figure 1 shows the correlation between AI, ML, and DL.

There are limitations in using AI in various areas of medicine. Looking back on many studies and applications of irrelevant databases having biases can influence the truthfulness of AI. Therefore, it is essential to design a bias-free, proposed, well-designed multicenter collaborative study, and various important aspects, such as economics, medical professional regulation, and ethical reviews, should not be ignored. Various terms associated with AI in this minireview are given in Table 1.

USE OF AI IN HCC DIAGNOSIS

The utility of AI can enhance diagnostic procedures in the area of liver cancer. CNN in the form of multilayered ANN is interlinked, and whole input data passes through every layer before being transformed to give output data. It is a more advanced version of DL that has its own learning capacity. Ultrasound (US) tests, abdominal computed tomography (CT), magnetic resonance imaging (MRI) of the abdomen, positron emission tomography (PET), and histology can benefit from CNN.
Table 1 Various terminology associated with artificial intelligence

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
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<tbody>
<tr>
<td>AI</td>
<td>The utilization of computers and associated techniques to mimic the sharp attitude and critical approach of humans</td>
</tr>
<tr>
<td>ML</td>
<td>It is a branch of AI and computer science that concerns the usage of data and algorithms to mimic the means that human beings ascertain and step by step upgrading its precision</td>
</tr>
<tr>
<td>ANN</td>
<td>It is a computational model in accordance with the structure and functions of biological neural networks. ANNs employ a nonlinear function to a loaded sum of inputs and model relations among them</td>
</tr>
<tr>
<td>CNN</td>
<td>It is a deep learning neural network intended to process structured arrays of data, <em>i.e.</em> radiological images</td>
</tr>
<tr>
<td>Deep learning</td>
<td>A branch of ML that tries to mimic the human brain and has the ability to gather data and do predictions with remarkable precision</td>
</tr>
<tr>
<td>AUC</td>
<td>AUC is an approach applied in ML to assess many used models to find out which have the higher performance</td>
</tr>
<tr>
<td>Accuracy</td>
<td>AI and ML technology employ algorithms to analyze data and perform predictions on the basis of such data. Although studies report that AI programs may regularly achieve accuracy levels of at least 95% and AI programs cannot verify the veracity of the data being examined, the overall accuracy is typically lower yet still higher than 80%</td>
</tr>
<tr>
<td>C-index (c-statistic)</td>
<td>It is an algorithm performance metric that takes values between 0 and 1 and explains how well the model fits the data</td>
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Figure 1  Relationship between artificial intelligence, machine learning, and deep learning.

**Ultrasound of the abdomen**

HCC develops in cirrhotic livers most of the time but not always. Clinical practice recommendations advocate routine abdominal US in hepatic cirrhosis patients. This approach is used for detecting lesions that occupy space. US is the primary machine for detecting hepatic disease and fresh lesions. Though, analysis of images is not straightforward and can be subject to interobserver variations.

To review the fundamental disorder, Bharti *et al.*[11] established an ANN model that discriminated various phases of hepatic infection by analyzing US images: normal liver, chronic liver disease, cirrhosis, and HCC. Further, this model’s accuracy was found to be 96.6%[11]. An algorithm to analyze US images was developed by Liu *et al.*[12]. Liu *et al.*[12] preferred the liver capsule to detect the existence of cirrhosis, even at an early stage when radiological findings are not clearly visible. By investigating the morphology of the liver capsule, Liu *et al.*[12] predicted the presence or absence of cirrhosis with an area under the curve (AUC) of 0.968.

The human output is defined when it comes to identifying liver lesions from US images. Schmauch *et al.*[13] developed a DL approach that could reveal and label benign and malignant space-occupying liver lesions. This system requires acceptance. It has the potential to improve the diagnostic yield of US and inform clinicians about potentially malignant lesions[13].
To improve the ability of contrast-enhanced US (C-US) for the detection of cancer-related characteristics, the use of AI has been utilized. Guo et al.[14] confirmed how applying DL to the behavior of liver lesions observed on C-US in three phases (arterial, portal, and late) improved the accuracy, sensitivity, and specificity of the investigation undertaken.

**Abdominal CT scan with intravenous contrast**

When an US reveals a fresh liver lesion, further imaging procedures, primarily dynamic contrast-enhanced CT or MRI, are used to get an accurate diagnosis. In dynamic CT or MRI scans, the radiological behavior of liver lesions can be used to characterize the lesion. If CT scans of liver nodules reveal unclear behavior, then lesion biopsy is prescribed as per the recommendation of the European Association for the Study of the Liver guidelines.[15] As suggested by the American Association for the Study of Liver Diseases guidelines,[16] there is the possibility of non-detection of a malignant lesion involved during the procedure or during close follow-up. A study was performed on 178 patients with cirrhosis and liver nodules by Mokrane et al.[17] and they were unable to differentiate between neoplastic and non-neoplastic lesions in these patients, hence requiring a biopsy. On doing a biopsy, 77% of the lesions were malignant. By applying DL techniques, the AUC for classifying nodules as HCC or non-HCC was 0.70. By analyzing the output of three-layered ANN, Yasaka et al.[18] with the help of contrast-enhanced CT classified liver masses into five groups: A (cholangiocarcinoma, hepatocellular carcinoma, or metastasis); B (other malignant tumors, i.e. cholangiocarcinoma, hepatocellular carcinoma, or metastasis); C (ambiguous masses, dysplastic nodules, or early HCC, and benign masses other than cysts or haemangiomas); D (haemangiomas); and E (cysts).

Assessing tumor load could be beneficial for detecting tumor relapse in follow-up CT scans. Vivanti et al.[19] proposed an automated detecting procedure for recurrence on the basis of early manifestation of the tumor, its CT behavior, baseline tumor load/mass quantification, and follow-up. With an accuracy of 86%, this approach demonstrated a higher proportion of true positives in detecting tumor relapse.

The usefulness of liver segmentation in assessing lesions in the liver and managing good treatment is critical. Li et al.[20] developed a CNN that could cause the segmentation of liver tumors on the basis of CT images having an accuracy of 82.67% ± 1.43%, which is better than existing approaches, allowing for more appropriate treatment planning.

**Abdominal MRI**

The use of CNN in MRI has also been investigated. Hamm et al.[21] prepared and verified a CNN-based DL approach that identified MRI liver lesions with 92% accuracy, 92% sensitivity, and 98% specificity with a mean computation time of 5.6 milliseconds.

Further research has used more MRI sequences, risk components, and clinical information of the patient to create an automated classification method that classifies hepatic lesions as adenoma, cyst, haemangioma, HCC, and metastasis, having sensitivity/specificity of 0.80/0.78, 0.93/0.93, 0.84/0.82, 0.73/0.56, and 0.62/0.77 respectively.[22]

**PET**

Preis et al.[23] used a neural network to study hepatic intake of fluorodeoxyglucose 18F along with data from the patient and clinical details to assess the results of 18F-FDG PET/CT (Fluorine 18 fluorodeoxyglucose positron emission tomography/computed tomography). Preis et al.[23] obtained higher sensitivity and specificity to find malignancy of the liver, which remained unrevealed visibly. This method can help the radiologist in the analysis of PET.

**Histology**

Even for experienced pathologists, determining the histopathological categorization of a liver lesion and distinction of tumor strain is critical to planning the treatment and prognosis assessment of the disease. Kiani et al.[24] were concerned with the histopathological distinction between HCC and cholangiocarcinoma and employed AI to assist pathologists.

Others reported how a deep CNN can perform an automatic identification of HCC and discriminate normal tissue from malignant tissue as well as identify key biological predictors, utilizing previous histopathological images of HCC.[25]

**USE OF AI FOR TREATING HCC**

The specific biological variance among HCC patients hampers evidence-based clinical assessment among all patients. Hence, for optimizing treatment techniques and measuring the results, powerful standardized risk classification tools are required. AI has the potential to play a significant role in the treatment of HCC in this area. The majority of studies about the applicability of AI in HCC treatment are focused on analyzing specific tumor attributes, i.e. radiological, histological, or genetic traits, or combining clinical data to estimate treatment response. Therefore, patients will be able to be better
selected for certain treatment alternatives.

**Use of radiomics**

The examination and remedy measure of HCC is generally performed with imaging facilities i.e. C-US, CT, and MRI following investigation of assured tumor characteristics, i.e. vascularization or behavior after the addition of a contrasting substance[26]. These attributes are amenable to biases after analysis by radiologists, along with the absence of high-resolution dimensional images. Recently an advanced technology has emerged in the area of radiology and cancer which is known as radiomics[27]. This technology extracts a large amount of significant data from the radiological images and links this data with the related biological system. The study of complete data with AI software can give effective and accurate reports for proper diagnosis and prognosis[27,28]. Figure 2 shows various stages of radiomics where AI can play a role.

**Assessment of surgical resection**

The early reappearance of the tumor following operative removal is due to an unsatisfactory prognostic process. The recognition of clinical cases before surgical operation with more risk of relapse is essential to escape irrelevant treatment. Various computer models help to analyze specific tumor markers/features and assist in the prognosis of the risk of relapse before operative procedures. These models also help in the assessment of survival after surgical removal.

Vascular microinvasion (VMI) is a self-sufficient prognostic component of relapse. VMI is linked with poor outcomes following tumor excision[29]. The accessibility of data regarding VMI preoperatively can be of high use. The radiological approach presently used in medical practice does not give a fair diagnosis.

Several studies explain radiomic signatures that presume the status of VMI preoperatively on the basis of contrast-enhanced CT[30,31] or MRI[32]. These techniques include exposure to radiation, are hard to execute, and are expensive. In a recent study, Dong et al[33] used grayscale US images based on radiomic algorithms to proceed with radiomic signatures in the prediction of VMI. By using radiomic techniques, Ji et al[34] developed prognostic models for relapse after excision surgery for assessing contrast-enhanced CT images and had a C-index value of 0.633-0.699. These models could be utilized for providing an individualized risk stratification for managing HCC individually.

ML techniques help in assessing survival after surgical resection as observed in many studies[35-37]. Recently, more advanced DL models helped in assessing survival after surgical resection on the basis of digitalized histological images of tumors.

**Assessment of transcathetet arterial chemoembolization**

According to Barcelona Clinical Liver Cancer (BCLC) classification, transcatheter arterial chemoembolization (TACE) exists as the preferred option for the treatment of intermediary B stage HCC[38]. The right choice of patients who can get benefit from this treatment is critical in order to minimize superfluous investigations that can lead to unfavorable side effects and waste healthcare resources. Studies based on AI approaches have been created as a trial to infer the feedback of TACE treatment and facilitate the proper selection of patients. The majority of the studies rely on image analysis, but some studies have also utilized genomic signatures. Morshid et al[39] developed an automatic ML algorithm that predicted TACE response using a mixture of quantitative CT image attributes and pretreatment patient clinical data. They obtained a prediction accuracy rate of 74.2% while working on combining the Barcelona Clinic Liver Cancer stage and quantitative image characteristics instead of applying the Barcelona Clinic Liver Cancer stage alone. Peng et al[40] used CT scans from 789 patients from three separate hospitals to verify a DL model for predicting TACE response. They were able to predict complete responses with an accuracy of 84% and an AUC of 0.97. Liu et al[41] developed and verified a DL radiomics-based C-US approach as a result of a quantitative assessment of C-US cine recordings. They demonstrated a high level of reproducibility and an AUC of 0.93 (95% confidence interval: 0.80-0.98) for predicting TACE reaction.

Further research has combined MRI and clinical data with ML approaches to predict TACE response. Abajian et al[42] worked on 36 patients who had an MRI prior to TACE. They built a response prediction model with 78.0% accuracy, 62.5% sensitivity, and 82% specificity.

The efficacy of TACE has also been tested by a post-treatment survival analysis of patients. Mähringer-Kunz et al[43] designed an ANN with every variable of main traditional prediction scores to produce a survival prediction model following TACE (ART[44], ABCR[45], and SNACOR[46]). With an AUC of 0.77, 78% sensitivity, and 81% specificity, they expected a 1-year survival rate that was better than the conventional scores.

Although radiomics have been used in the majority of investigations estimating the usage of AI to examine TACE. Some have also looked at genetic analysis to predict TACE response. Ziv et al[47] analyzed genetic mutations by applying SVM algorithms to look for tumor responses following TACE. However, this study involved a small number of cases.
Radiofrequency ablation evaluation
Radiofrequency ablation has also been studied as a treatment for HCC in its early stages. Liang et al. [48] used SVM to create a prognostic model of HCC relapse. They investigated 83 HCC cases that had undergone radiofrequency ablation and secured an AUC of 0.69, 67% sensitivity, and 86% specificity. From this data, they could recognize patients with a greater chance of relapse.

HCC OVERALL SURVIVAL PREDICTION
Apart from the use of any therapy, AI approaches have been used to predict the overall survival of HCC patients. The observations by Dong et al.[49] were based on current information on the relationship between anomalies in DNA methylation and HCC[50-52]. They employed ML techniques (SVM) for the evaluation of DNA methylation data from 377 HCC samples and created three risk groups to expect complete survival and achieved a mean 10-fold cross-validation score of 0.95.

FUTURE PERSPECTIVES
To illustrate the effectiveness of AI for medical assistance, further research is required that compares the output of medical staff with AI assistance vs experts lacking AI assistance. These studies should target elements linked to curing and prognosis (for instance, identifying ambiguous hepatic wounds, the existence of vascular invasion, and the reaction to percutaneous treatments) to analyze liver masses and explore HCC. Additional significant points are the utilization of AI for interpretation of HCC behavior in cirrhotic and non-cirrhotic patients, in the differential diagnosis of primary and metastatic liver lesions[53], and particularly in the clinical detection of cholangiocarcinoma, which is difficult to differentiate from HCC with existing approaches and has distinct treatment methods from HCC. Simultaneously, healthcare providers must be trained for the integration of AI into everyday practice in the area of liver cancer.

SIGNIFICANCE OF THE STUDY
AI has guided the detection of HCC (on the basis of premalignant variations, imaging, and biomarkers) as a result of its capability to examine huge datasets and combine data effectively. The perspective of AI techniques is immense in every stage in the handling of HCC, e.g., from early diagnosis to treatment options and prognostic and therapeutic response prognosis. These methods could promote accurate and personalized medicine to assist clinical practice and better utilize healthcare resources. Numerous datasets (radiological images or pathologic data) could be utilized individually or in conjunction for accuracy better than that of conventional statistical means. Moreover, AI-based approaches can also assist in lowering interobserver variance while studying images and leads to standardization.

INNOVATIVE CONTRIBUTIONS OF THE STUDY
The outcomes from many studies endorse the consolidation of the ML models with clinical/pathologic data and created clinical scores or biomarkers. Biomarkers detected by the incorporation of several ‘-omics’ datasets lead to the recognition of a biochemical tumor signature, which revolutionizes HCC detection in the near future.

CONCLUSION
One of the most significant advancements in recent years has been the utilization of AI technologies in medicine. It will almost certainly grow in popularity as a result of its utility in processing and analyzing...
massive amounts of available data. However, we should be attentive that there are some limitations that may reduce its acceptability and application in the medical field. Medical professionals need to understand the genuine value of AI and recognize the necessity for it to coexist with the essential requirement for human assessment. Regardless of the significant advancements, it is critical to ensure that medical protocols remain completely transparent.

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FOOTNOTES

Author contributions: Mokhria RK designed the outline, performed data acquisition, contributed to the majority of the writing, and proofread the paper; Singh J coordinated the writing of the paper and proofread the paper.

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REFERENCES


Ho WH, Lee KT, Chen HY, Ho TW, Chiu HC. Disease-free survival after hepatic resection in hepatocellular carcinoma patients: a prediction approach using artificial neural network. *PLoS One* 2012; **7**: e29179 [PMID: 22352720 DOI: 10.1371/journal.pone.0029179]
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10.1371/journal.pone.0029179


Dietary counseling based on artificial intelligence for patients with nonalcoholic fatty liver disease

Yumi Kusano, Kei Funada, Mayumi Yamaguchi, Miwa Sugawara, Masaya Tamano

Abstract

BACKGROUND
About 25% of the general population in Japan are reported to have nonalcoholic fatty liver disease (NAFLD). NAFLD and nonalcoholic steatohepatitis carry a risk of progressing further to hepatocellular carcinoma. The primary treatment for NAFLD is dietary therapy. Dietary counseling plays an essential role in dietary therapy. Although artificial intelligence (AI)-based nutrition management software applications have been developed and put into practical use in recent years, the majority focus on weight loss or muscle strengthening, and no software has been developed for patient use in clinical practice.

AIM
To examine whether effective dietary counseling is possible using AI-based nutrition management software.

METHODS
NAFLD patients who had been assessed using an AI-based nutrition management software application (Calomeal) that automatically analyzed images of meals photographed by patients and agreed to receive dietary counseling were given dietary counseling. Blood biochemistry tests were performed before (baseline) and 6 mo after (6M follow-up) dietary counseling. After the dietary counseling, the patients were asked to complete a questionnaire survey.

RESULTS
A total of 29 patients diagnosed with NAFLD between August 2020 and March 2022 were included. There were significant decreases in liver enzyme and triglyceride levels at the 6M follow-up compared to baseline. The food analysis
capability of the AI used by Calomeal in this study was 75.1%. Patient satisfaction with the AI-based dietary counselling was high.

CONCLUSION

AI-based nutrition management appeared to raise awareness of dietary habits among NAFLD patients. However, it did not directly alleviate the burden of registered dietitians, and improvements are much anticipated.

Key Words: Artificial intelligence; Dietary counselling; Nonalcoholic fatty liver disease; Nonalcoholic steatohepatitis; Nutrition management software applications

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Core Tip: Use of artificial intelligence (AI)-based nutrition management software (Calomeal) appeared to raise awareness of nonalcoholic fatty liver disease patients’ dietary habits, and they showed significant decreases in liver enzyme and triglyceride levels at the 6-mo follow-up compared to baseline. The food analysis capability of the AI package used in this study was 75.1%, and patient satisfaction with the AI-based dietary counselling was high. However, due to the limitations of the food analysis capabilities of AI, it did not directly alleviate the burden of registered dietitians, and improvements in the analytical capabilities of AI are much anticipated.

INTRODUCTION

About 25% of the general population in Japan are reported to have nonalcoholic fatty liver disease (NAFLD), and this figure is expected to increase to 39.3% by 2030[1]. NAFLD includes nonalcoholic fatty liver (NAFL) and nonalcoholic steatohepatitis (NASH). NAFL and NASH carry a risk of progressing further to hepatocellular carcinoma. Although the risk of developing liver cancer from NAFL is low (0.44 per 1000 persons per year), the risk increases with the progression of liver pathology (5.29 per 1000 persons per year in patients with NASH and 0.45 to 22.6 per 1000 persons per year in patients with liver cirrhosis)[2,3].

The primary treatment for NAFLD is dietary therapy. Dietary counseling plays an essential role in dietary therapy. In dietary counseling, patients self-report all the food items that they consumed over the previous 1 wk, and during the interview, registered dietitians calculate the caloric and nutritive values of the food items. Limitations exist with patients’ memory certainty and the listening and calculation skills of the dietitians in the field. In recent years, pictures taken with digital cameras have been used in combination with interviews. Neither of these is very efficient, because dietary counseling begins when patients come in for their consultation, and the caloric and nutrient intakes are calculated based on patients’ recalled food items consumed in the past.

Artificial intelligence (AI)-based image analysis has penetrated deeply in our daily lives, and the field of medicine is no exception. In gastroenterology, it is used to diagnose colon polyps, Helicobacter pylori infection, and stomach cancer[4-8]. Although AI-based nutrition management software applications have been developed and put into practical use in recent years, the majority focus on weight loss or muscle strengthening, and no software has been developed for patient use in clinical practice.

Thus, the present study examined whether effective dietary counseling is possible using food intake data of NAFLD patients that had been automatically analyzed with an AI-based nutrition management software application.
Patients clinically diagnosed with NAFLD between August 2020 and March 2022 were included as subjects. NAFLD was diagnosed when fatty liver was observed in patients with an alcohol consumption equivalent to ≤ 30 g of ethanol per day in men and ≤ 20 g of ethanol per day in women [9]. Fatty liver was diagnosed when the following three criteria were confirmed on abdominal ultrasound examination: (1) Increased hepatic echogenicity; (2) positive liver-kidney contrast; and (3) deep ultrasonic attenuation in the liver. Patients with chronic hepatitis B, chronic hepatitis C, autoimmune hepatitis, and primary biliary cholangitis were excluded. Patients with non-compensated liver cirrhosis and those with concomitant hepatocellular carcinoma were also excluded.

**Dietary counseling using AI**

“Calomeal” is a software application developed by Life Log Technology, Inc. (Tokyo, Japan) that can easily record and manage one’s daily meals and physical activity. It has been available in Japan since December 2015. The “Calomeal” software is commercially available, and anyone can purchase it. When a user takes a picture of a meal using devices such as smartphones, the cloud-based AI calculates the nutritive values of the food in the photograph, and the results are sent to the user’s device (Figure 1). The AI of Calomeal was compiled using machine learning of food image data collected from major restaurant chains, food manufacturers, and everyday home-cooked meals. It can identify approximately 18000 food images. In addition to total caloric intake, Calomeal simultaneously calculates the nutritive values of proteins, lipids, carbohydrates, glucides, dietary fiber, and salt content.

This study used a customized version of Calomeal that was developed in cooperation with Life Log Technology. The following three areas were customized: (1) Changing the device from a smartphone to an iPad Mini; (2) simplifying food selection and offering more detailed options on consumed quantities; and (3) redirecting the AI analysis results to the study’s dedicated personal computer and not to the patients’ devices.

More specifically, since some NAFLD patients were older, iPad Minis were used as the device instead of smartphones because iPad Minis have larger display screens (Figure 2). When patients took pictures of a food item, the AI suggested the name of three possible food choices. The patients then selected from the three choices the food item that they consumed. When none of the offered three choices matched, “no suitable choice” was selected. Next, the patients chose the quantity of food that they consumed from the list of options. Eight options were available. Setting 100% as the normal serving size, the options were as follows: 200%, 150%, 100%, 66% (about two-thirds), 50%, 33% (about one-third), 10% (about one bite), and 0% (although a picture was taken, no food was consumed). AI calculated the nutritive values once these tasks were completed. The analysis results were forwarded to the study’s dedicated personal computer managed by the authors (Figure 3). Breakfast, lunch, dinner, or snacks were automatically determined based on the time when the foods were photographed.

After photographing one week’s worth of pictures of meals, the patients came in for their dietary counseling session. By the time of the patients’ visits, the AI had prepared a list of a patient’s one week’s worth of photographed foods (Figure 4) and bar charts showing the amounts of caloric, protein, lipid, carbohydrate, glucose, dietary fiber, and salt intakes (Figure 5). Registered dietitians participating in this study conducted dietary counseling while presenting the abovementioned data.

The photographed food images for which the patients could not find a suitable choice at the time of taking the picture were examined by the registered dietitians before the patients’ visits, and after checking the photographed images, the registered dietitians entered the correct item name.

**Principle of Calomeal**

Around dozens of pieces of photograph data for one food (or one product) are prepared for machine learning. These photographs are learned by deep neural network, and foods (or a product) are analyzed by the pattern of the color and form.

The nutrient of common foods was calculated based on “standard table of food composition” announced by Japanese Ministry of Education, Culture, Sports, Science and Technology by dietitian of Life Log Technology company. The nutrient of foods of major restaurant chains and food manufacturers was calculated using the data published in the home page of each company. When the nutrient was not announced in home page of the company, the dietitian calculated the nutrient from announced raw materials.

**Effects of dietary counseling using Calomeal**

Of all the patients enrolled in the study, patients who agreed to receive dietary counseling were given dietary counseling using Calomeal. Blood biochemistry tests were performed before (baseline) and 6 mo after (6M follow-up) dietary counseling. Aspartate aminotransferase (AST), alanine aminotransferase (ALT), γ-glutamyltransferase (GGT), total cholesterol (T-cho), and triglyceride (TG) levels were compared between the baseline and 6M follow-up.

Body weight of all patients was compared between the baseline and 6M follow-up.

**Analysis capability of AI**

As noted earlier, the AI used in the present study was capable of analyzing approximately 18000 meal
Figure 1  The concept of Calomeal. When users take a photograph of their meals with their smartphones, the artificial intelligence on the Calomeal server calculates the nutritive value of the food included in the photograph, and the results are sent to the user’s device.

Figure 2  Display on the iPad Mini. Instead of using a smartphone as the device, an iPad Mini, which has a larger screen, is used. When a patient photographs a food item, the artificial intelligence suggests the names of three possible food choices. The patient selects the food that he or she ate from one of the three choices. If none of the three choices matches, the patient chooses “no suitable choice.” Next, the patient selects the quantity of food consumed from the list of options. Eight options are available. Setting 100% as the normal serving size, the choices are as follows: 200%, 150%, 100%, 66% (about two-thirds), 50%, 33% (about one-third), 10% (about one bite), and 0% (picture was taken but no food was consumed). Breakfast, lunch, dinner, or snacks are automatically determined based on the time that the foods were photographed.

items. However, since most of these items were collected from menus of major restaurant chains and food manufacturers, its ability to identify everyday home-cooked meals was unknown. The AI’s ability to analyze food images was evaluated by calculating the percentage (%) of unidentified foods (i.e., foods for which the results of the AI’s automated analysis did not match the foods actually consumed by the patients, thereby categorized under “no suitable choice”) among all food items.

In addition, the time spent by registered dietitians before the patient visits in entering the correct food names of the unidentified “no suitable choice” food items was also measured.

Acceptance of Calomeal

After the dietary counseling, subjects in the Calomeal Group were asked to complete a questionnaire survey consisting of the following questions:

Question 1: Were you glad that you were given an AI-based dietary counseling session? (Yes or No).
Question 2: Did you find the dietary counseling rewarding? (Yes or No).
Question 3: Have you become more conscious of improving your dietary lifestyle? (Yes or No).
Figure 3 Calomeal concepts that were customized in this study. The food images photographed with an iPad Mini are analyzed by the artificial intelligence on the Calomeal server. The following information is sent to the dedicated personal computer at the authors’ hospital: ID, basic information of patients, captured food images, food lists of last one week, calculation of nutritive value, and bar charts of the nutritive value. Registered dietitians conduct dietary counseling based on these data.

Question 4: Would you like to receive another AI-based dietary counseling session? (Yes or No).

**Statistical analysis**
Continuous data, such as those from the blood biochemistry tests, are shown as the mean ± standard deviation. The paired Wilcoxon test was used to test the difference in each parameter between the start of observation (baseline) and after 6 mo (6M follow-up). \( P < 0.05 \) was considered significant.

**RESULTS**
There were 29 patients who agreed and received dietary counseling using Calomeal. The operation of Calomeal using iPads was accepted by all 29 patients. Table 1 shows the patients’ characteristics. The patients had been taking all of these medications before starting this study, and no new drugs were initiated after the start of the observation in this study.

**Effects of dietary counseling**
Table 2 shows the AST, ALT, GGT, hemoglobin A1c (HbA1c), T-cho, and TG levels and body weight at baseline and 6M follow-up. AST, ALT, GGT, and TG levels were significantly lower (\( P = 0.0088, 0.0133, 0.0494, \) and 0.0246, respectively) at the 6M follow-up compared to the levels at baseline. Body weight was significantly lower (\( P = 0.0472 \)) at the 6M follow-up compared to that at baseline.

**Analysis capability of AI**
Table 3 shows the total number of food items photographed in 1 wk of all patients in the Calomeal Group, the number of food items categorized under “no suitable choice”, and the food analysis capability of the AI. The mean number of total photographed food items was 62.6 (20 to 104), the mean number of food items categorized under “no suitable choice” was 15.0 (1 to 32), and the mean analysis capability was 75.1% (51.5 to 98.6%). Before dietary counseling sessions, registered dietitians spent on average 25.9 min (4.5 to 67.0 min) identifying the food items categorized under “no suitable choice.”

**Acceptance of Calomeal**
Table 4 shows the findings of the responses to the questionnaire survey. When the patients were asked “Were you glad that you were given an AI-based dietary counseling session?” in Question 1, all 29 patients said “Yes.” When the patients were asked “Did you find the dietary counseling rewarding?” in Question 2, 15 of the 29 patients responded “Yes.” When the patients were asked “Have you become more conscious of improving your dietary lifestyle after the dietary counseling session?” in Question 3, all 29 patients responded “Yes.” When the patients were asked “Would you like to receive another AI-based dietary counseling session?” in Question 4, four of the 29 patients responded “No.”
### Table 1 Patients’ characteristics (n = 29)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male/Female</td>
<td>16/13</td>
</tr>
<tr>
<td>Age (yr)</td>
<td>56.4 ± 14.3</td>
</tr>
<tr>
<td>Body weight (kg)</td>
<td>74.1 ± 13.1</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td>28.4 ± 5.2</td>
</tr>
<tr>
<td>Metabolic diseases</td>
<td></td>
</tr>
<tr>
<td>Diabetes mellitus (Yes/No)</td>
<td>10/19</td>
</tr>
<tr>
<td>Dyslipidemia (Yes/No)</td>
<td>14/15</td>
</tr>
<tr>
<td>Concomitant drugs</td>
<td></td>
</tr>
<tr>
<td>SGLT2 inhibitor</td>
<td>2</td>
</tr>
<tr>
<td>DPP-4 inhibitor</td>
<td>3</td>
</tr>
<tr>
<td>Thiazolidinedione</td>
<td></td>
</tr>
<tr>
<td>GLP-1 agonist</td>
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</tr>
<tr>
<td>Statin</td>
<td>7</td>
</tr>
<tr>
<td>Bezafibrate</td>
<td></td>
</tr>
<tr>
<td>Pemafibrate</td>
<td></td>
</tr>
<tr>
<td>EPA and DHA preparation</td>
<td>1</td>
</tr>
<tr>
<td>AST (U/L)</td>
<td>50.2 ± 33.4</td>
</tr>
<tr>
<td>ALT (U/L)</td>
<td>53.8 ± 39.0</td>
</tr>
<tr>
<td>GGT (U/L)</td>
<td>80.3 ± 84.3</td>
</tr>
<tr>
<td>T-B (mg/dL)</td>
<td>1.3 ± 0.9</td>
</tr>
<tr>
<td>Alb (mg/dL)</td>
<td>4.2 ± 0.6</td>
</tr>
<tr>
<td>eGFR (mL/min)</td>
<td>71.1 ± 11.5</td>
</tr>
<tr>
<td>HbA1c (%)</td>
<td>6.4 ± 0.8</td>
</tr>
<tr>
<td>T-cho (mg/dL)</td>
<td>191.3 ± 35.0</td>
</tr>
<tr>
<td>TG (mg/dL)</td>
<td>126.5 ± 57.8</td>
</tr>
<tr>
<td>WBC (10³/μL)</td>
<td>5.6 ± 1.5</td>
</tr>
<tr>
<td>Hb (g/dL)</td>
<td>14.5 ± 1.7</td>
</tr>
<tr>
<td>Plts (10⁴/μL)</td>
<td>17.7 ± 7.4</td>
</tr>
</tbody>
</table>


### DISCUSSION

AI helps diagnose NAFLD through its use in diagnostic imaging procedures such as ultrasound, computed tomography, and magnetic resonance imaging and pathological diagnostic procedures[10-12]. However, there have been no reports of using AI in nutritional therapies and dietary counseling for NAFLD. Thus, the authors focused on this aspect and planned the present study.

There is a long history of using AI in food analysis. In 1983, Chen et al.[13] reported that the caloric intake of foods could be calculated using a small wearable computer that can be attached to clothing like a tin badge. This small computer called the eButton is being used for the healthy transformation of homemade foods[14,15]. When the eButton is used solely for identifying foods, the sensitivity is 85.0% and the specificity is 85.8%. Since the small eButton can be worn by attaching it to clothing, privacy is maintained[13]; however, its widespread use by the general public may be difficult because it is a purpose-built computer.

In Japan, there are five types of nutrition management software applications that can be downloaded on smartphones. Although there may be some differences in their analysis capability, all of them are very easy to use[16]. Of these software applications, Oka et al.[17] used Asken for dietary counseling of
Table 2 Changes of blood biochemistry parameters and body weight

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>6M Follow-up</th>
<th>P value</th>
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</thead>
<tbody>
<tr>
<td>AST (U/L)</td>
<td>50.2 ± 33.4</td>
<td>34.7 ± 14.7</td>
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<tr>
<td>ALT (U/L)</td>
<td>53.8 ± 39.0</td>
<td>35.3 ± 16.8</td>
<td>0.0113</td>
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<tr>
<td>GGT (U/L)</td>
<td>80.3 ± 84.3</td>
<td>66.3 ± 82.9</td>
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<tr>
<td>HbA1c (%)</td>
<td>6.4 ± 0.8</td>
<td>6.2 ± 0.6</td>
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<tr>
<td>T-cho (mg/dL)</td>
<td>191.3 ± 35.0</td>
<td>189 ± 34.3</td>
<td>0.2109</td>
</tr>
<tr>
<td>TG (mg/dL)</td>
<td>126.5 ± 57.8</td>
<td>104.1 ± 60.6</td>
<td>0.0426</td>
</tr>
<tr>
<td>Body weight (kg)</td>
<td>74.0 ± 13.1</td>
<td>71.2 ± 12.3</td>
<td>0.0472</td>
</tr>
</tbody>
</table>


Figure 4 Analysis results of the photographed food images. A list is created based on the results of the artificial intelligence calculation using food names and intakes (%) selected by patients. Energy, protein, lipid, carbohydrate, salt, glucose, and dietary fiber content of each meal over 1 wk are shown.

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type 2 diabetes mellitus patients and reported its benefit. Of these five software applications, the present study focused on Calomeal. The main reason for choosing Calomeal was its ease of operation.

In the present study, significant decreases in AST, ALT, GGT, and TG levels and body weight were observed at the 6M follow-up compared to the levels at baseline. However, there is an important limitation of this study. The present study did not compare dietary counseling using conventional methods with dietary counseling using Calomeal. The reason was that, in contrary to the authors’ expectations, fewer patients gave consent for dietary counseling after being diagnosed with NAFLD during the study period. Thus, it cannot be asserted that this study’s dietary counseling using Calomeal is superior to conventional methods. This issue needs to be addressed in future research.

The food analysis capability of the AI used by Calomeal in this study was 75.1%. The food analysis capability using Life Log Technology’s own data was reported to be 85.7%, which showed a discrepancy with the present study’s findings. One possible reason may be the small percentage of data for everyday
Table 3 Number of photographed food items, analysis rate, and time for confirmation

<table>
<thead>
<tr>
<th>Case</th>
<th>All foods</th>
<th>No of candidates</th>
<th>Analysis rate (%)</th>
<th>Time for confirmation (min)</th>
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<td>1</td>
<td>57</td>
<td>13</td>
<td>77.2</td>
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<tr>
<td>2</td>
<td>31</td>
<td>2</td>
<td>93.5</td>
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<tr>
<td>3</td>
<td>90</td>
<td>31</td>
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<td>67.0</td>
</tr>
<tr>
<td>4</td>
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<td>7</td>
<td>82.5</td>
<td>20.5</td>
</tr>
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<td>5</td>
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</tr>
<tr>
<td>Average</td>
<td>62.6</td>
<td>15.0</td>
<td>75.1</td>
<td>25.9</td>
</tr>
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</table>

Table 4 Questionnaire results

<table>
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<th>No</th>
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</thead>
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<tr>
<td>1</td>
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</tr>
<tr>
<td>2</td>
<td>15</td>
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</tr>
<tr>
<td>4</td>
<td>25</td>
<td>29</td>
</tr>
</tbody>
</table>

home-cooked meals, since the food items registered in Calomeal’s AI consisted primarily of major restaurant chain menus, food manufacturers’ items, and convenience store products. In the present study, NAFLD patients, especially elderly patients, often consumed unique homemade dishes whose food names were difficult to identify just by looking at the pictures.
In other words, there were various daily diets, especially the cooking methods of family diets cannot be unified. These made food illegible and energy intake difficult to calculate. This can lead to significant error in the study.

Assuming that a patient eats four dish items per meal, three meals a day, this means that $4 \times 3 \times 7 = 84$ items should have been photographed in 1 wk. However, as shown in Table 2, there was a large difference among patients, some with very few photographed food items (20 items) and some who had photographed many food items (104 items). The following reasons were given: (1) Patients could not take pictures while they were dining out because they were conscious of their surroundings; (2) patients could not bring the iPads to work; and (3) Japanese “teishoku” set lunches often plate various dishes on one plate, and some patients took pictures of the whole plate as one photograph. In the case of (3), the AI could not analyze multiple food items at once. This issue was reported to Life Log Technology as feedback, and the Calomeal software at the time of writing this paper had already taken this into account.

In the present study, the names of all food images that patients selected as “no suitable choice” on the screen were examined and entered individually by the registered dietitians. This procedure, which on average took 25.9 min (4.5 to 67.0 min), was conducted before the dietary counseling sessions. Since the duration of one dietary counseling session was 30 min, this means that preparation required about the same amount of time. However, when meeting the patient face-to-face, a list of food items pho-
tographed by the patient over the previous 1 wk and bar charts of various nutrients were already prepared. Thus, it is possible that more productive dietary counseling was offered within the allocated 30-min session.

The questionnaire results showed that all of the respondents said that they were glad to have undergone dietary counseling using Calomeal. Similarly, they all responded that they had become aware of their dietary habits. On the other hand, 15 of 29 patients found the content of the dietary counseling rewarding. The majority of patients in the Calomeal Group in this study had a good command of their smartphones, and these patients had free access to the internet. Perhaps there was a lack of originality in the hospital-based dietary counseling, since nutritional information, to some extent, is available when one searches the internet. When the patients were asked whether they would like to receive dietary counseling again using Calomeal, four patients responded “No.” During outpatient follow-up interviews, all four patients commented that they “did not want to bring the devices out of their homes or to work.” This issue could be resolved by changing the device to a smartphone.

CONCLUSION
When an AI-based nutrition management software application automatically analyzed images of meals photographed by NAFLD patients, there were significant decreases in AST, ALT, GGT, and TG levels after 6 mo (6M follow-up). Thus, this method appeared to raise awareness of dietary habits of NAFLD patients. On the other hand, due to the limitations of the food analysis capabilities of AI, it did not directly alleviate the burden of registered dietitians, and improvements in the analytical capabilities of AI are much anticipated.

ARTICLE HIGHLIGHTS
Research background
Approximately 27000 people a year die from liver cancer in Japan. Liver cancer from non-viral liver disease increases while cancerogenesis from viral liver decreases. In the non-viral liver disease, nonalcoholic fatty liver disease (NAFLD) increases in particular. Therefore, carcinogenesis restraint from NAFLD is urgent business to reduce liver cancer death. Diet therapy is the first choice for the treatment of NAFLD and nutrition education for this purpose becomes extremely important.

Research motivation
The authors paid attention to the nutrition education using the artificial intelligence and led to the idea of this study using the application software called the "Calomeal". The authors have the patients understand the importance of the diet by performing the nutrition education using the artificial intelligence for the NAFLD patients and want to help inhibit the cancerogenesis from NAFLD. A study on optimization of the nutrition education using the artificial intelligence (AI) for NAFLD is the attempt that leads the world and thinks with pioneer positioning of the future health promotion medical care.

Research objectives
Patients clinically diagnosed with NAFLD between August 2020 and March 2022 were included as subjects. "Calomeal" as a software application developed by Life Log Technology, Inc. (Tokyo, Japan) was used for the nutrition education. Blood biochemistry tests were performed before (baseline) and 6 mo after (6M follow-up) dietary counseling. After the dietary counseling, the patients were asked to complete a questionnaire survey.

Research methods
There were significant decreases in liver enzyme and triglyceride levels at the 6M follow-up compared to baseline. The food analysis capability of the AI used by Calomeal in this study was 75.1%. Patient satisfaction with the AI-based dietary counselling was high.

Research results
The authors have the patients understand the importance of the diet because the NAFLD patients receive a nutrition education using the artificial intelligence, and the purpose of this study is to carry a help of the cancerogenesis restraint.

Research conclusions
When an AI-based nutrition management software application automatically analyzed images of meals photographed by NAFLD patients, liver function was improved significantly. On the other hand, due to the limitations of the food analysis capabilities of AI, improvements in the analytical capabilities of AI
are much anticipated.

**Research perspectives**
The direction of future research is nutrition education using more advanced artificial intelligence to inhibit the carcinogenesis from NAFLD.

**FOOTNOTES**

**Author contributions:** Kusano Y reviewed the literature and contributed to manuscript drafting; Funada K analyzed and interpreted the imaging findings; Yamaguchi M drafted the tables and figures; Sugawara M conducted dietary counseling for patients; Tamano M revised the manuscript for important intellectual content; all authors issued final approval for the version to be submitted.

**Institutional review board statement:** Approval was obtained from the Biomedical Ethics Committee of the authors’ affiliated hospital (No. 2014).

**Clinical trial registration statement:** The clinical trial is registered with clinical research support office of the authors’ affiliated hospital. Details can be found at https://dept.dokkyomed.ac.jp/dep-k/gast/.

**Informed consent statement:** Written informed consent was obtained from all patients for publication of this report and any accompanying images.

**Conflict-of-interest statement:** None of the authors have any commercial or financial involvements in connection with this study that represent or appear to represent any conflicts of interest.

**Data sharing statement:** Participants gave informed consent for data sharing.

**CONSORT 2010 statement:** The authors have read the CONSORT Statement—checklist of items, and the manuscript was prepared and revised according to the CONSORT Statement—checklist of items.

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**REFERENCES**


Kusano Y et al. AI-based dietary counseling for NAFLD


