Supplementary Note 1 – Search terms

Pubmed (January 19th 2021): 6869 hits

(pancreas[tiab] OR pancreatic[tiab] OR rectal[tiab] OR rectum[tiab] OR colon*[tiab] OR colorectal[tiab] OR gastric[tiab] OR abdominal*[tiab] OR visceral*[tiab] OR thyroid*[tiab] OR spleen[tiab] OR esophag*[tiab] OR oesophag*[tiab] OR liver[tiab] OR hepatic[tiab] OR gastric*[tiab] OR stomach[tiab] OR kidney[tiab] OR gallbladder[tiab] OR intestine*[tiab])

AND (adenocarcinom*[tiab] OR carcinom*[tiab] OR cancer*[tiab] OR "malignant growth"[tiab] OR tumor[tiab] OR tumors[tiab] OR tumour*[tiab] OR tumorous[tiab] OR neoplas*[tiab] OR sarcom*[tiab] OR oncolog*[tiab])

OR "Abdominal Neoplasms"[Mesh] OR "Digestive System Neoplasms"[Mesh]

AND

(surger*[tiab] OR surgical*[tiab] OR resect*[tiab] OR operat*[tiab] OR treatment*[tiab] OR excision*[tiab] OR dissection*[tiab] OR "surgical procedures, operative"[MeSH terms])

OR (pancreaticoduodenectom*[tiab] OR pancreatoduodenectom*[tiab] OR duodenopancreatectom*[tiab] OR pancreatectom*[tiab] OR Whipple[tiab] OR esophagectom*[tiab] OR oesophagectom*[tiab] OR hepatectom*[tiab] OR colectom*[tiab] OR splenectom*[tiab] OR thyroidectom*[tiab] OR cholecystectom*[tiab] OR gastrectom*[tiab])

OR "Abdominal Neoplasms/surgery"[Mesh] OR "Digestive System Neoplasms/surgery"[Mesh]

AND ("decision support techniques"[MeSH] OR "Decision Support Systems, Clinical"[Mesh] OR "artificial intelligence"[MeSH] OR ("decision support"[tiab] AND (technique*[tiab] OR system*[tiab] OR tool*[tiab] OR model*[tiab])) OR "decision aid"[tiab] OR "decision making"[tiab] OR "prediction model"[tiab] OR "Bayesian model" [tiab] OR "decision Analytical Modeling"[tiab] OR "decision Analytic Model"[tiab] OR "decision analysis" [tiab] OR "artificial intelligence"[tiab] OR "Machine Learning"[tiab] OR "deep learning"[tiab] OR "neural network"[tiab] OR "neural networks" [tiab] OR "Neural Networks, Computer"[Mesh] OR ("Case based"[tiab] AND reason*[tiab]))

AND 2011:2020[dp]

NOT (animals [mh] NOT humans [mh])

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TS = (pancreas OR pancreatic OR rectal OR rectum OR colon* OR colorectal OR gastric OR abdominal* OR visceral* OR thyroid* OR spleen OR esophag* OR oesophag* OR liver OR hepatic OR gastric* OR stomach OR kidney OR gallbladder OR intestine*)

AND TS = (adenocarcinom* OR carcinom* OR cancer* OR "malignant growth" OR tumor OR tumors OR tumour* OR tumorous OR neoplas* OR sarcom* OR oncolog*)

AND

TS = (surger* OR surgical* OR resect* OR operat* OR treatment* OR excision* OR dissection*)

OR TS = (pancreaticoduodenectom* OR pancreatoduodenectom* OR duodenopancreatectom* OR pancreatectom* OR Whipple OR esophagectom* OR oesophagectom* OR hepatectom* OR colectom* OR splenectom* OR thyroidectom* OR cholecystectom* OR gastrectom*)

AND TS = ("decision support" NEAR/6 (technique* OR system* OR tool* OR model*))

OR TS = ("decision aid" OR "decision making" OR "prediction model" OR "Bayesian model" OR "decision Analytical Modeling" OR "decision Analytic Model" OR "decision analysis" OR "artificial intelligence" OR "machine Learning " OR "deep learning" OR (neural NEAR/3 network*)

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(pancreas OR pancreatic OR rectal OR rectum OR colon* OR colorectal OR gastric OR abdominal* OR visceral* OR thyroid* OR spleen OR esophag* OR oesophag* OR liver OR hepatic OR gastric* OR stomach OR kidney OR gallbladder OR intestine*):ti,ab,kw

AND (adenocarcinom* OR carcinom* OR cancer* OR "malignant growth" OR tumor OR tumors OR tumour* OR tumorous OR neoplas* OR sarcom* OR oncolog*):ti,ab,kw

OR MeSH descriptor: [Abdominal Neoplasms] explode all trees OR MeSH descriptor: [Digestive System Neoplasms] explode all trees

AND

(surger* OR surgical* OR resect* OR operat* OR treatment* OR excision* OR dissection*):ti,ab,kw

OR MeSH descriptor: [Surgical Procedures, Operative] explode all trees

OR (pancreaticoduodenectom* OR pancreatoduodenectom* OR duodenopancreatectom* OR pancreatectom* OR Whipple OR esophagectom* OR oesophagectom* OR hepatectom* OR colectom* OR splenectom* OR thyroidectom* OR cholecystectom* OR gastrectom*):ti,ab,kw

OR MeSH descriptor: [Abdominal Neoplasms] explode all trees and with qualifier(s): [surgery - SU] OR MeSH descriptor: [Digestive System Neoplasms] explode all trees and with qualifier(s): [surgery - SU]

AND MeSH descriptor: [Decision Support Techniques] explode all trees OR MeSH descriptor: [Decision Support Systems, Clinical] explode all trees OR MeSH descriptor: [Artificial Intelligence] explode all trees

OR ("decision support" AND (technique* OR system* OR tool* OR model*)):ti,ab,kw

OR ("decision aid" OR "decision making" OR "prediction model" OR "Bayesian model" OR "decision Analytical Modeling" OR "decision Analytic Model" OR "decision analysis" OR "artificial intelligence" OR "Machine Learning " OR "deep learning") :ti,ab,kw

OR (neural NEAR/3 network*):ti,ab,kw OR ("Case based" NEAR/3 reason*):ti,ab,kw OR MeSH descriptor: [Neural Networks, Computer] explode all trees

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Supplementary Table 1. PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Page 1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Page 3
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Page 5
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Page 6
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Page 6,7
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Page 7,8
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Supplement

Section and Topic	Item #	Checklist item	Location where item is reported
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Page 8
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Page 8
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Page 8
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Page 8
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Page 8

Section and Topic	Item #	Checklist item	Location where item is reported
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Page 8
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Page 8
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Page 8
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Page 10,11
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Page 8
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Page 8
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Page 8
Reporting	14	Describe any methods used to assess risk of bias due to missing results in a synthesis	Page 8

Section and Topic	Item #	Checklist item	Location where item is reported
bias assessment		(arising from reporting biases).	
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Page 8
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Page 12
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Page 13
Study characteristics	17	Cite each included study and present its characteristics.	Supplement
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	n.a. See page 8
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Supplement

Section and Topic	Item #	Checklist item	Location where item is reported
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	n.a., see page 8
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	n.a., see page 8
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	n.a., see page 8
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	n.a., see page 8
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	n.a., see page 8
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	n.a., see page 8
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Page 18
	23b	Discuss any limitations of the evidence included in the review.	Page 18-21

Section and Topic	Item #	Checklist item	Location where item is reported
	23c	Discuss any limitations of the review processes used.	Page 21
	23d	Discuss implications of the results for practice, policy, and future research.	Page 20,21
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Page 6
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Page 6
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Page 6
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Page 9,10
Competing interests	26	Declare any competing interests of review authors.	Page 23
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Page 9

From: Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 2021;372:n71. doi: 10.1136/bmj.n71

For more information, visit: http://www.prisma-statement.org/

Supplementary Table 2. Overview of studies included in this systematic review

Author	Year	Tumor entity	Purpose/ Prediction	Multiple algorithms	ROC AUC	Interface	Open source	Summary of clinical application
Gohari et al. [1]	2011	Colorectal	Survival	Yes	0.730	No	No	Prediction of 1-, 3- and 5-year survival in colorectal cancer patients after surgical treatment.
van Stiphout et al.[2]	2011	Colorectal	Complete response	No	0.690	No	No	Prediction of pathological complete response to chemoradiation therapy for colorectal cancer. Three different models were developed, one using clinical features, one using clinical and pre-therapy features and one using clinical, pre-therapy and post-therapy features. Prediction could

								guide the decision for additional surgery for colorectal cancer.
Stojadinovic et al.[3]	2011	Colorectal	Survival	No	0.711	No	No	Prediction of survival in patients with colon cancer considered for cytoreductive surgery and hyperthermic intraperitoneal chemotherapy for peritoneal carcinomatosis.
Biglarian et al.[4]	2012	Colorectal	Metastasis	Yes	0.820	No	No	Prediction of distant metastasis in colorectal cancer.
Stojadinovic et al.[5]	2013	Colorectal	Survival	No	0.850	No	No	Survival prediction for 12, 24, 36 and 60 months for colon cancer after therapy.
Spelt et al.[6]	2013	Colorectal	Survival	Yes	N/A	No	No	Prediction of survival with Cox-regression and ANN after the resection of liver metastasis in colorectal

								cancer.
Adams and Papagrigoriadis[7]	2014	Colorectal	Postoperative complications	No	N/A	(Yes)	Yes	Prediction of anastomotic leakage as a postoperative complication.
Francis et al.[8]	2015	Colorectal	Delayed discharge, readmission	Yes	0.817	No	No	Prediction of delayed discharge and readmission in an enhanced-recovery program for colorectal surgery patients.
Peng et al.[9]	2016	Colorectal	Survival	Yes	N/A	(Yes)	No	Prediction of 10-year survival with three different ANN and one ANN model combining the previous three after surgery for colon cancer.
Pourahmad et al.[10]	2016	Colorectal	Staging	Yes	N/A	No	No	Prediction of cancer stage with clustering algorithms before surgery.
Soguero-Ruiz	201	Colorectal	Postoperative	Yes	0.94	No	No	Prediction of anastomotic

et al.[11]	6		complications		0			leakage with SVM using free-text-documents, vital signs, and laboratory values in surgery for colorectal cancer. Combination of different data sources yielded the best results.
Soguero-Ruiz et al.[12]	2016	Colorectal	Postoperative complications	Yes	N/A	No	No	Prediction of anastomotic leakage using SVM and bag-of-words in free-text documents in surgery for colorectal cancer.
Fujino et al.[13]	2017	Colorectal	Postoperative complications	No	0.792	No	No	Prediction of high-output ileostomy as postoperative complication after surgery for colorectal cancer.
Sa et al.[14]	2017	Colorectal	Staging	No	0.891	No	No	Preoperative prediction of T-stage for colorectal cancer.
Stoean et	201	Colorectal	Hospital stay	Yes	N/A	No	No	Predicting the length-of-stay

al.[15]	7							with several machine learning methods in surgery for colorectal cancer.
van Soest et al.[16]	2017	Colorectal	Complete response	No	0.700	No	No	Prospective validation of a previously published method on predicting pathological complete response in esophageal cancer patients (van Stiphout et al.).
Arostegui et al.[17]	2018	Colorectal	Mortality	Yes	0.835	No	No	Prediction of 1-year mortality of patients who survived for 30 days after their operation for colon cancer.
Ichimasa et al.[18]	2018	Colorectal	Lymph node invasion	Yes	0.821	No	No	Prediction of lymph node metastases for T1-colorectal cancer and guidance for decision between sole endoscopic resection or additional surgery.

Bjarnadottir et al.[19]	2018	Colorectal	Mortality	Yes	0.839	(Yes)	No	Prediction of mortality in 30 days, 180 days and 1-, 1.5-, 2-, 2.5-, 3, 3.5-, 4-, 4.5-, and 5-years after diagnosis of colorectal cancer. Development of a web application with features available before treatment to ensure useability.
Saso et al.[20]	2018	Colorectal	Disease free survival	No	0.552	No	No	Prediction of disease-free survival after resection of Stage-II-Colon cancer.
Al-Bahrani et al.[21]	2019	Colorectal	Survival, conditional survival	Yes	0.862	Yes	Yes	Prediction of 1-, 2-, and 5-year survival and conditional survival.
Curtis et al.[22]	2019	Colorectal	Time to surgery	No	0.641	No	Yes	Prediction of time to surgery for patients with colorectal cancer stratifying them in groups to be operated on in

								<4, <8, and <12 weeks.
PelvEx Collaborative[23]	2020	Colorectal	Postoperative complications, survival, prediction R0, hospital stay	Yes	0.707	No	No	Prediction of R0-resection, length of stay, 30-day postoperative complications, and 1-year survival with 3 algorithms (LR, SVM, ANN) in patients with pelvic exenteration.
Ting et al.[24]	2020	Colorectal	Second primary tumor	Yes	0.723	No	No	Prediction of developing second primary colorectal cancer after surgical treatment for the first cancer.
Xu et al.[25]	2020	Colorectal	Recurrence	Yes	0.761	No	No	Prediction of cancer recurrence in stage IV colorectal cancer after resection of the primary tumor.
Cowling et	202	Colorectal	Mortality	Yes	0.81	No	No	Prediction of 1-year mortality

al.[26]	0				1			with boosted trees and logistic regression using patients´demographics and ICD-10 codes from a public database after colorectal surgery. Logistic regression performed slightly better than boosted tree-models.
Huang et al.[27]	2020	Colorectal	Complete response	Yes	0.840	No	No	Prediction of pathological complete response in rectal cancer after neoadjuvant therapy. ML-algorithms could help to decide whether additional surgery is necessary.
Kudo et al.[28]	2020	Colorectal	Lymph node invasion	No	0.830	No	No	Prediction of lymph node metastasis in T1 colorectal cancer after endoscopic resection to prevent unnecessary additional

								surgery for lymph nodes. Comparison of the ANN with current US and Japanese guidelines with ANN performing significantly better.
Li et al.[29]	2020	Colorectal	Survival	Yes	0.792	No	No	Prediction of 3- and 5-year survival with different algorithms and an ensemble algorithm that combined the others after resection of colorectal cancer. Performance of the ensemble algorithm was better than standard Cox-regression model and AJCC TNM staging.
Moro et al.[30]	2020	Colorectal	Survival	Yes	N/A	No	No	Utilization of CART-algorithm to determine which clinical

								factors are associated with long term survival in hepatectomy for colorectal liver metastasis. Mutational status of KRAS leads to different features being responsible for long-term survival according to the CART algorithm.
Sha et al.[31]	2020	Colorectal	Mortality	Yes	0.970	No	No	Identification of risk factors responsible for in-hospital mortality in patients undergoing surgery for colorectal cancer. ANN was able to better identify features responsible than logistic regression.
Tian et al.[32]	2020	Colorectal	Survival	No	0.783	(Yes)	No	Prediction of 5-year survival with multisource transfer learning in colorectal cancer

								after surgery. The selected method can improve generalizability in the development of prediction models.
Wang et al.[33]	2020	Colorectal	Treatment response	Yes	0.898	No	No	Construction of a nomogram for partition of patients with colorectal cancer treated with neoadjuvant therapy in good and bad responders. The nomogram was constructed using radiomic and clinical features and outperformed RF-models.
Merath et al.[34]	2020	Colorectal, Liver, Pancreas	Postoperative complications	No	0.740	No	No	Prediction of 30-day postoperative complications with decision trees after surgery for liver, pancreatic, or colorectal cancer.

Yang et al.[35]	2013	Esophagus	Metastasis	Yes	N/A	No	No	Construction of four SVM models to predict postoperative distant metastases after the resection of esophageal cancer.
Rice et al.[36]	2017	Esophagus	Lymph node invasion	No	N/A	No	No	Data mining approach to identify predictors for pN+, number of positive nodes, pN-classification and extent of lymphadenectomy to detect pN+ in esophageal cancer.
Takeuchi et al.[37]	2018	Esophagus	Survival, disease free survival	Yes	0.724	No	No	Prediction of survival and disease-free survival after surgery for esophageal cancer.
Shao et al.[38]	2019	Esophagus	Postoperative complications	No	0.950	No	No	Prediction of anastomotic leakage with features available after

								esophagectomy.
Rice et al.[39]	2019	Esophagus	Treatment selection	No	N/A	No	No	Decision and selection of therapy by choosing the therapy predicted to maximize the survival of an individual patient with cancer of esophageal-gastric junction.
Rahman et al.[40]	2020	Esophagus	Recurrence	Yes	0.804	Yes	Yes	Prediction of early recurrence (< 1 year) after neoadjuvant therapy and resection of esophageal cancer.
Bolourani et al.[41]	2020	Esophagus	Readmission	Yes	0.740	No	No	Prediction of early readmission (< 30 days) before discharge with readily available data after esophagectomy. Development of 2 random forest models both performing better than

								logistic regression.
Chen et al.[42]	2020	Esophagus	Lymph node invasion	Yes	0.960	No	No	Prediction of lymph node metastasis with LR and ANN in order to select patients suited for an endoscopic treatment rather than surgery with lymphadenectomy.
Liu et al.[43]	2020	Esophagus	Lymph node invasion	No	0.852	No	No	Prediction of lymph node metastasis in cT1-2 esophageal squamous cell cancer.
Wang et al.[44]	2020	Esophagus	Survival	Yes	N/A	No	No	Prediction of survival in patients with esophageal squamous cell carcinoma with routine blood parameters taken before surgery.
Xu et al.[45]	2021	Esophagus, Stomach, Colorectal	Postoperative complications	Yes	N/A	No	No	Prediction of postoperative fatigue in patients for different gastrointestinal

								tumors before surgery.
Wu et al.[46]	2020	Gallbladder	Survival	Yes	0.765	No	No	Prediction of survival for more or less than 20 months in patients that underwent surgery for gallbladder carcinoma. The models used features that were available after resection.
Tsilimigras et al.[47]	2020	Intrahepatic cholangio-carcinoma	Survival	No	N/A	No	No	Patients with intrahepatic cholangiocarcinoma were clustered with an unsupervised ML algorithm in different groups using preoperatively available features. Survival among the groups differed significantly. Construction of a classification tree that was able to group patients in the identified clusters.

Tsilimigras et al.[48]	2020	Intrahepatic cholangio-carcinoma	Survival	No	0.670	No	No	A CART-algorithm was utilized to stratify patients with intrahepatic cholangiocarcinoma in different survival groups using preoperatively available features.
Bhandari et al.[49]	2020	Kidney	Intraoperative, postoperative complications	Yes	0.858	No	No	Prediction of intra- and 30-day postoperative complications after surgery for kidney cancer.
Cucchetti et al.[50]	2010	Liver	Vascular invasion, grading	Yes	0.900	Yes	No	Prediction of microvascular invasion and tumor grade with ANN and statistical methods for hepatocellular carcinoma before operation.
Ho et al.[51]	2012	Liver	Disease free survival	Yes	0.777	No	No	Prediction of 1-, 3-, and 5-year disease free survival with several machine learning

								algorithms after surgery for liver cancer.
Shi et al.[52]	2012	Liver	Mortality	Yes	0.840	No	No	Prediction of in-hospital-mortality after surgery for liver cancer.
Zhang et al.[53]	2012	Liver	Mortality	No	N/A	No	No	Prediction of 1-, 2-, and 5-year mortality with preoperatively available features in liver transplantation for hepatocellular carcinoma.
Shi et al.[54]	2012	Liver	Mortality	Yes	0.890	No	No	Prediction of 5-year mortality in liver resections for hepatocellular carcinoma.
Chiu. H. C. et al.[55]	2013	Liver	Survival	Yes	0.875	No	Yes	Prediction of 1-, 3-, and 5-year survival after surgery for hepatocellular carcinoma.
Qiao et al.[56]	201	Liver	Survival	Yes	0.82	No	No	Prediction of survival with an

	4				9			ANN after partial hepatectomy. Comparison to a Cox-regression model and common staging systems.
Santos[57]	2015	Liver	Survival	Yes	0.700	No	No	Prediction of 1-year survival in hepatocellular carcinoma with features available before treatment. Use of methods to account for small patient sample sizes.
Tanaka et al.[58]	2015	Liver	Recurrence	No	0.580	No	No	Data-mining analysis with decision-tree was used to identify groups with low- and high-risk for recurrence after liver transplantation for hepatocellular carcinoma. Preoperative available features were used to stratify patients to the mentioned groups and the model was

								compared to the Milan-Criteria with favorable results for the decision tree.
Cai et al.[59]	2015	Liver	Survival	No	N/A	No	No	Prediction of survival in liver cancer with a Bayesian Network using preoperative and postoperative values. The Bayesian Network was used to identify features responsible for a prolonged survival after hepatectomy.
Ogihara et al.[60]	2016	Liver	Recurrence	No	N/A	No	No	Prediction of early recurrence after complete resection of liver cancer and comparison with already published scores.
Chiu. C. C.. et al.[61]	2018	Liver	Quality of life	Yes	N/A	No	No	Prediction of quality of life after surgery for liver cancer.
Xu et al.[62]	2019	Liver	Recurrence	Yes	N/A	No	No	Partition of patients in groups with early and late recurrence

								with several ML-algorithms using pre- and intraoperative features after hepatectomy for hepatocellular carcinoma.
Ivanecz et al.[63]	2019	Liver	Intraoperative complications	Yes	N/A	No	No	External validation of a previously published difficulty score (Halls et al.) for intraoperative complications in laparoscopic liver resection.
Lei et al.[64]	2020	Liver	Postoperative complications	Yes	0.725	No	Yes	Prediction of acute renal failure after resection for liver cancer.
Schoenberg et al.[65]	2020	Liver	Disease free survival	No	0.788	Yes	Yes	Prediction of early disease free survival with preoperatively available clinical features.
Tsilimigras et al.[66]	2020	Liver	Survival	No	N/A	No	No	Prediction of 5-year survival with preoperative features

								and with pre- and postoperative features in patients with hepatocellular carcinoma.
Cao et al.[67]	2020	Liver	Recurrence	Yes	N/A	No	No	Prediction of recurrence of hepatocellular carcinoma with an ensemble algorithm carcinoma. Feature selection was performed with Pearson-Correlation-Coefficient before applying the ensemble algorithm.
Iwahashi et al.[68]	2020	Liver	Recurrence	No	N/A	No	No	Prediction of recurrence of hepatocellular cancer after surgery.
Mai et al.[69]	2020	Liver	Postoperative complications	Yes	0.880	No	No	Prediction of postoperative hepatic liver failure with ANN and preoperatively available features.

								Comparison to a logistic regression model and several classification systems.
Ansari et al.[70]	2013	Pancreas	Survival	Yes	N/A	No	No	Prediction of survival with a model that combined several ANNs after the resection of pancreatic cancer.
Smith and Mezhir[71]	2014	Pancreas	Lymph node invasion, survival	Yes	N/A	Yes	Yes	Prediction of survival with a bayesian model for pancreatic cancer. The bayesian model combines predictions for lymph node ratio by LR with survival prediction by Cox-regression.
Velez-Serrano et al.[72]	2017	Pancreas	Mortality	No	0.910	No	No	Prediction of in-hospital mortality after the resection of pancreatic cancer.
Walczak and Velanovich[73	2017 &	Pancreas	Survival	Yes	0.658	No	No	Prediction of 7-month survival after the resection of

,74]	2018							pancreatic cancer using quality of life domains among other features.
Song et al.[75]	2018	Pancreas	Survival	Yes	0.870	No	No	Prediction of 5-year survival after surgery for pancreatic neuroendocrine tumors.
Bradley et al.[76]	2019	Pancreas	Survival	No	0.700	No	No	Prediction of 1-year survival before and after surgery for pancreatic cancer.
Sala Elarre et al.[77]	2019	Pancreas	Recurrence	Yes	0.750	No	No	Prediction of recurrence of pancreatic cancer after two years. Patients were treated with neoadjuvant therapy before surgery.
Lee et al.[78]	2020	Pancreas	Metastasis, prediction of futile Surgery	Yes	0.831	Yes	No	Prediction of occult metastases in (borderline) resectable pancreatic cancer and possible avoidance of futile surgery. Unclear

								combination of RF and LR to construct a nomogram to predict occult metastases/futile surgery.
Han et al.[79]	2020	Pancreas	Postop.complication	Yes	0.704	Yes	Yes	Prediction of postoperative pancreatic fistula with pre- and intraoperative features.
Kang et al.[80]	2020	Pancreas	Malignancy	Yes	0.725	No	No	Prediction of malignancy of intraductal IPMNs with different ML-algorithms and LR with both achieving similar performance results but LR being more convenient.
Roth et al.[81]	2020	Pancreas	Malignancy	No	0.920	No	No	Prediction of low- and high-risk IPMNs with SVM using preoperatively available clinical features and serum protein signature. Distinction

								in low- and high-risk may help in the decision whether surgery is necessary.
Zhang et al.[82]	2020	Pancreas	Postoperative complications	Yes	0.800	No	No	Prediction of admittance to ICU after pancreatectomy for pancreatic cancer. Additional models were developed for prediction of hours in the ICU, intraoperative blood loss, in-hospital stay and discharge costs. These models were not further described or evaluated.
Maubert et al.[83]	2019	Peritoneal carcinomatosis	Diagnosis, treatment selection	Yes	0.958	No	No	Prediction of resectability of peritoneal carcinomatosis with ML-methods using intraoperative assessment of different organ involvements.
Biglarian et	201	Stomach	Survival	Yes	0.92	No	No	Prediction of survival for 1-,

al.[84]	1				0			2-, 3-, 4-, and 5-years for patients with surgery for gastric cancer.
Amiri et al.[85]	2013	Stomach	Survival	Yes	N/A	No	No	Prediction of survival for 6, 12, 18, 24, 36, 48, and 60 months with Cox-Regression and three different ANN models.
Zhu et al.[86]	2013	Stomach	Survival	Yes	N/A	No	No	Prediction of survival with ANN for gastric cancer and comparison with Cox-proportional-hazard model.
Zhou et al.[87]	2013	Stomach	Lymph node invasion	Yes	0.829	No	No	Preoperative prediction of lymph node metastasis with radiological features extracted by radiologists.
Nilsaz-Dezfouli et al.[88]	2017	Stomach	Survival	Yes	0.962	No	No	Prediction of survival for 1-, 2-, 3-, 4-, and 5-years with

								censored patient data after surgery for gastric cancer.
Korhani and Bahrampour[89]	2018	Stomach	Survival	Yes	0.961	No	No	Prediction of survival with Bayesian Neural Network and ANN with the first performing better. Unclear timeframe for survival prediction.
Oh et al.[90]	2018	Stomach	Survival	No	0.800	No	No	Prediction of survival for up to 5 years with recurrent neural network that adjusted the survival prediction for the upcoming year according to the status of the patient and the prediction of the previous year.
Yazdani Charati et al.[91]	2018	Stomach	Survival	No	N/A	No	No	Prediction of survival after the treatment of gastric cancer.

Liu et al.[92]	2019	Stomach	Treatment selection	Yes	0.946	No	No	Surgical decision support to determine the extent of lymphadenectomy (D1 VS D2) in gastric cancer with machine-learning algorithms.
Lu et al.[93]	2019	Stomach	Postoperative complications	Yes	0.826	(Yes)	No	Prediction of postoperative complications in gastric cancer surgery using pre- and intraoperative features.
Neto et al.[94]	2019	Stomach	Postoperative complications, mortality	Yes	0.909	No	No	Prediction of mortality and postoperative complications in gastric cancer patients. Focus on different algorithms to improve prediction results rather than clinical focus.
Que et al.[95]	2019	Stomach	Survival	No	0.790	No	No	Prediction of 3-year survival for gastric cancer with preoperatively available features. Comparison with

								cTNM and pTNM staging.
Takeuchi et al.[96]	2019	Stomach	Lymph node invasion	No	0.860	No	No	Prediction of metastasis in non-sentinel lymph node basins when sentinel lymph nodes are affected by gastric cancer.
Li et al.[97]	2020	Stomach	Survival	No	0.791	No	No	Prediction of 5-year survival after gastrectomy for gastric carcinoma.
Akcay et al.[98]	2020	Stomach	Metastasis, recurrence, survival	Yes	0.820	No	No	Prediction of overall survival, distant metastasis, and peritoneal recurrence with various ML-algorithms and logistic regression after surgery and radiotherapy. For the different predictions Gaussian-Naive-Bayes, Multilayer-Perceptron Neural Network, and Random Forest

								performed best.
Zhou et al.[99]	2020	Stomach	Metastasis	Yes	0.745	No	Yes	Postoperative prediction of metachronous peritoneal metastasis with different machine learning algorithms after surgery for gastric cancer.
Liu et al.[100]	2011	Thyroid	Malignancy	No	N/A	No	No	Prediction of malignancy in suspect thyroid nodules.
Saylam et al.[101]	2013	Thyroid	Malignancy	Yes	0.824	No	No	Prediction of malignancy in thyroid cancer with indeterminate fine-needle-aspiration cytology.
Jajroudi et al.[102]	2014	Thyroid	Survival	Yes	N/A	No	No	Prediction of survival for 1-, 3-, and 5-years after therapy for thyroid cancer.
Pourahmad et	201	Thyroid	Malignancy	Yes	0.91	No	No	Prediction of malignancy in

al.[103]	5				0			thyroid nodules with neural network before surgery.
Ozden et al.[104]	2018	Thyroid	Lymph node invasion	Yes	0.786	No	No	Prediction of central lymph node metastasis in patients with papillary thyroid microcarcinoma.
Mourad et al.[105]	2020	Thyroid	Survival	Yes	0.945	No	No	Prediction of survival in thyroid cancer patients with three different multilayer-perceptron models after their treatment.
Placzek et al.[106]	2020	Thyroid	Malignancy	Yes	0.980	No	No	Prediction of malignancy in thyroid nodules with bayesian networks using clinical and molecular features. The model combining clinical and molecular features was the most promising predicting malignancy.

Seib et al.[107]	2020	Thyroid	Postoperative complications	Yes	0.720	No	No	Identification of patients who will suffer from neck hematoma, recurrent laryngeal nerve injury and hypocalcemia following thyroidectomy. An ensemble algorithm used preoperative factors to identify affected patients and performed better than a logistic regression model.
Wu et al.[108]	2020	Thyroid	Lymph node invasion	Yes	0.731	No	No	Prediction of central lymph node metastasis in patients with papillary thyroid cancer using preoperatively available features. Several ML-algorithms were tested with Gradient Boosting Decision Tree yielding the best results for performance

								and clinical utility in decision curve analysis.

In column "interface" studies describing an interface that was not publicly available are marked "(yes)". ROC: Receiver operating characteristic; ANN: artificial neural network; LR: logistic regression; SVM: support vector machine; RF: random forest; CART: classification and regression tree; IPMN: intraductal papillary mucinous neoplasm.

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