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(54) MACHINE LEARNING BASED DUPLICATE INVOICE DETECTION

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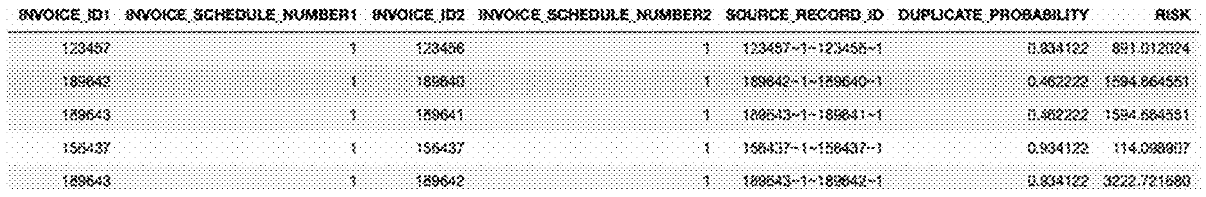
(57) ABSTRACT

Embodiments detect duplicate invoices, each invoice including a plurality of fields. Embodiments generate synthetic training data using a plurality of training invoices and generating one or more modified fields for each of the plurality of training invoices. Embodiments train a machine learning model using the synthetic training data and generate a plurality of candidate invoice pairs. Embodiments input the plurality of candidate invoice pairs to the trained machine learning model and generate, by the trained machine learning model, a prediction of whether each of the candidate invoices pairs is a duplicate invoice pair.



INVOICE_ID1	INVOICE_SCHEDULE_NUMBER1	INVOICE_ID2	INVOICE_SCHEDULE_NUMBER2	SOURCE_RECORD_ID	DUPLICATE_PROBABILITY	RISK
123457	1	123456	1	123457~1~123456~1	0.934122	891.012024
189642	1	189640	1	189642~1~189640~1	0.462222	1594.864551
189643	1	189641	1	189643~1~189641~1	0.462222	1594.864551
158437	1	158437	1	158437~1~158437~1	0.934122	114.098807
189643	1	189642	1	189643~1~189642~1	0.934122	3222.721680

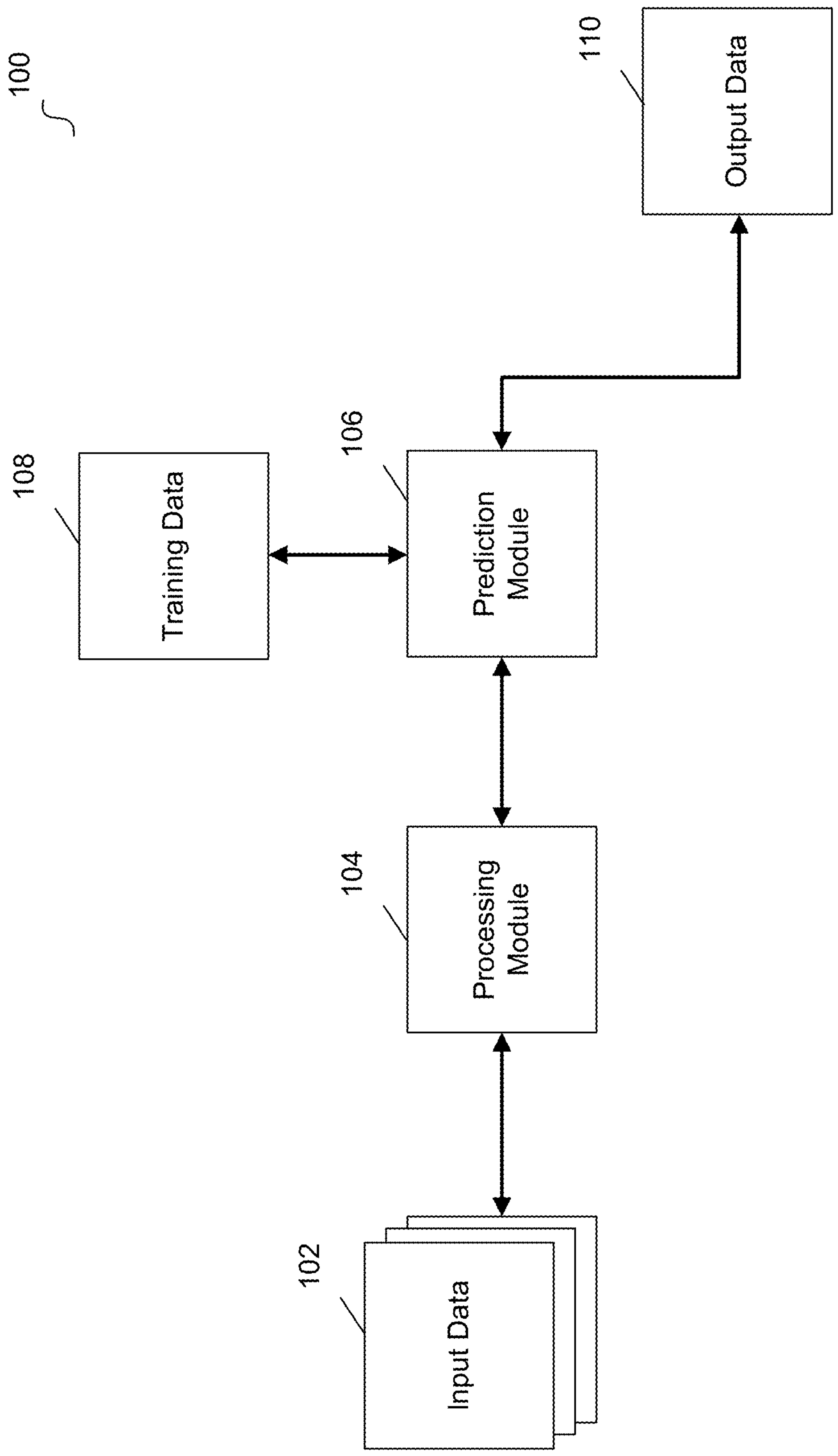

100
108
Training Data
106
Prediction Module
110
Output Data
104
Processing Module
102
Input Data

Fig. 1

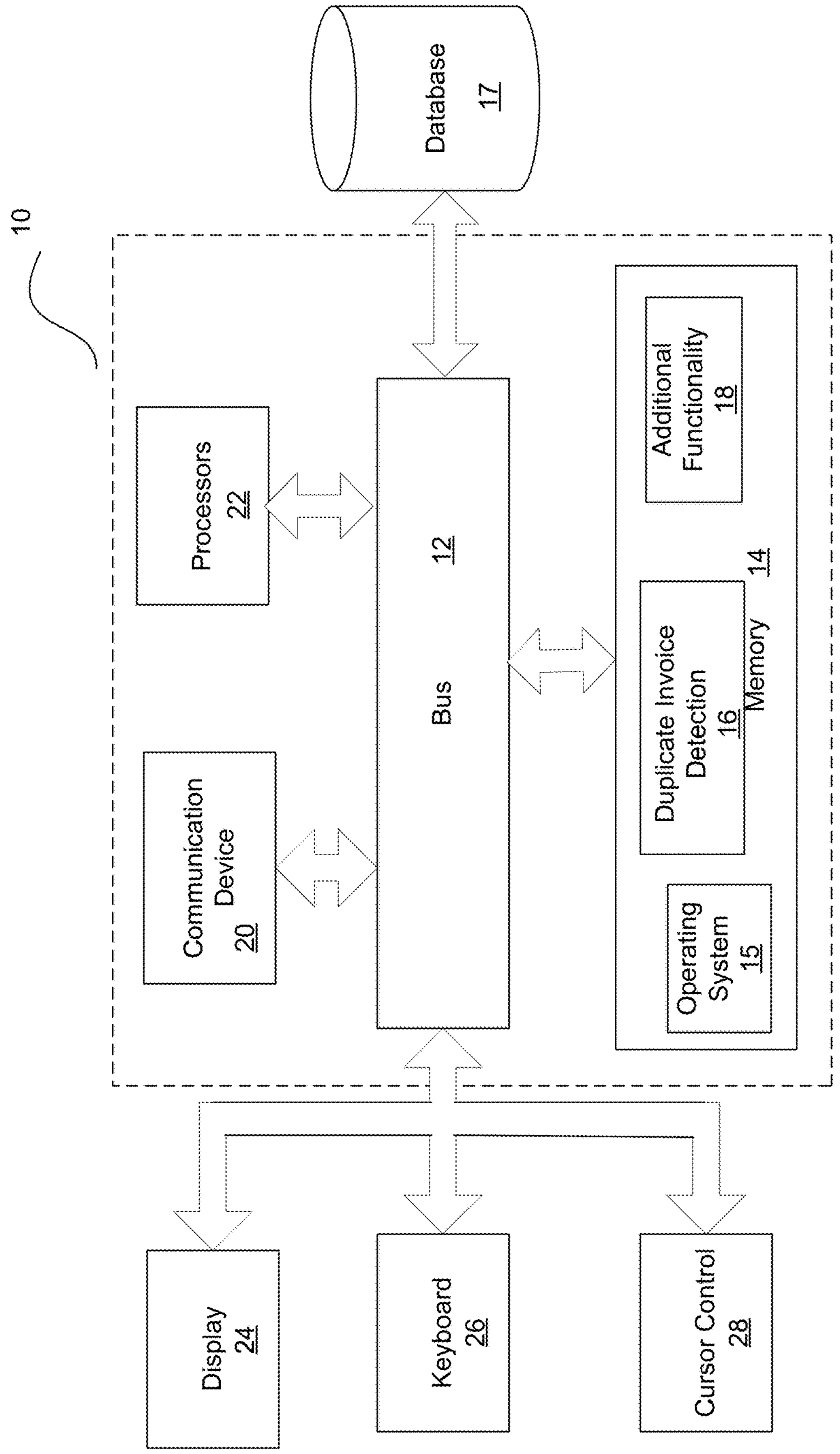
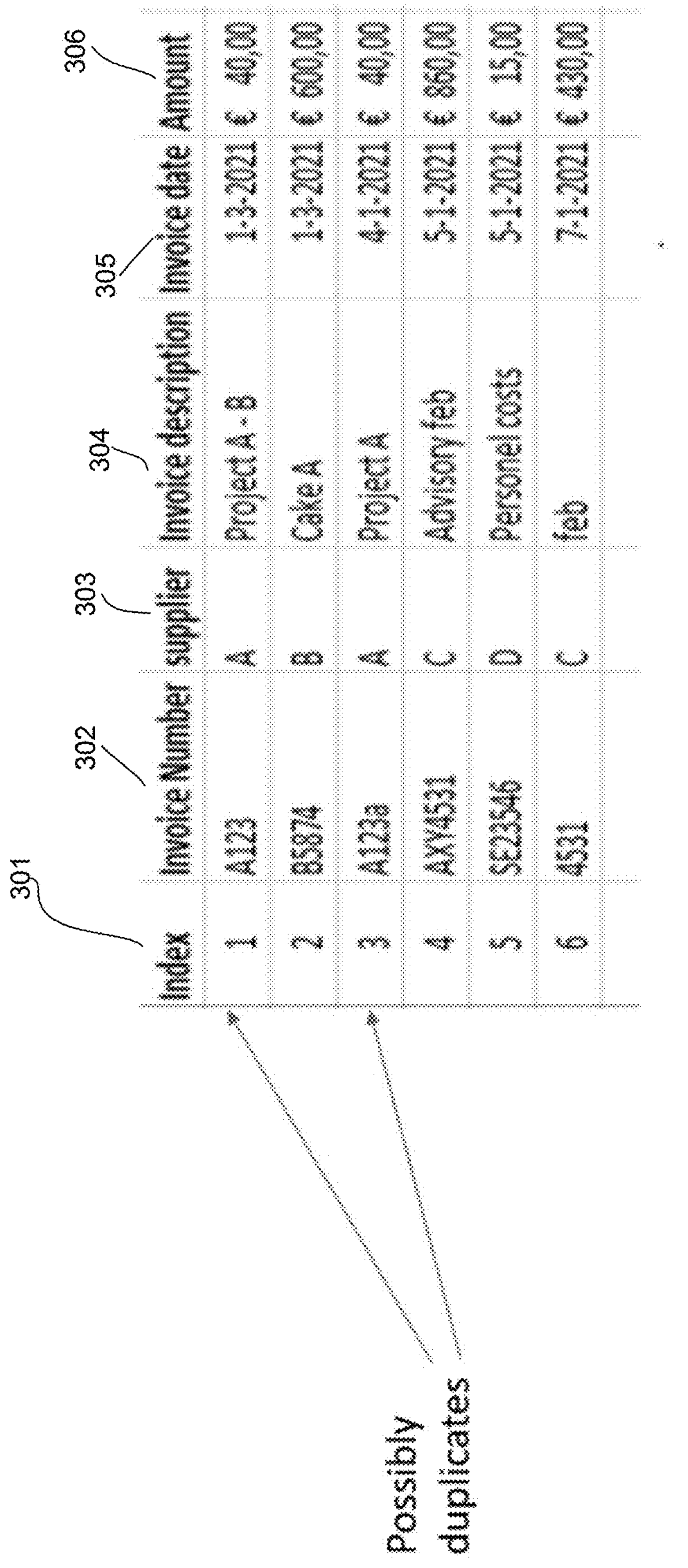

Database
17
10
Processors
22
Bus
12
Communication
Device
20
Additional
Functionality
18
14
Duplicate Invoice
Detection
16
Memory
Operating
System
15
Display
24
Keyboard
26
Cursor Control
28

Fig. 2


301
302
303
304
305
306
Possibly duplicates

Index	Invoice Number	supplier	Invoice description	Invoice date	Amount
1	A123	A	Project A - B	1-3-2021	€ 40,00
2	B5874	B	Cake A	1-3-2021	€ 600,00
3	A123a	A	Project A	4-1-2021	€ 40,00
4	AXY4531	C	Advisory feb	5-1-2021	€ 860,00
5	SE23546	D	Personel costs	5-1-2021	€ 15,00
6	4531	C	feb	7-1-2021	€ 430,00

Fig. 3

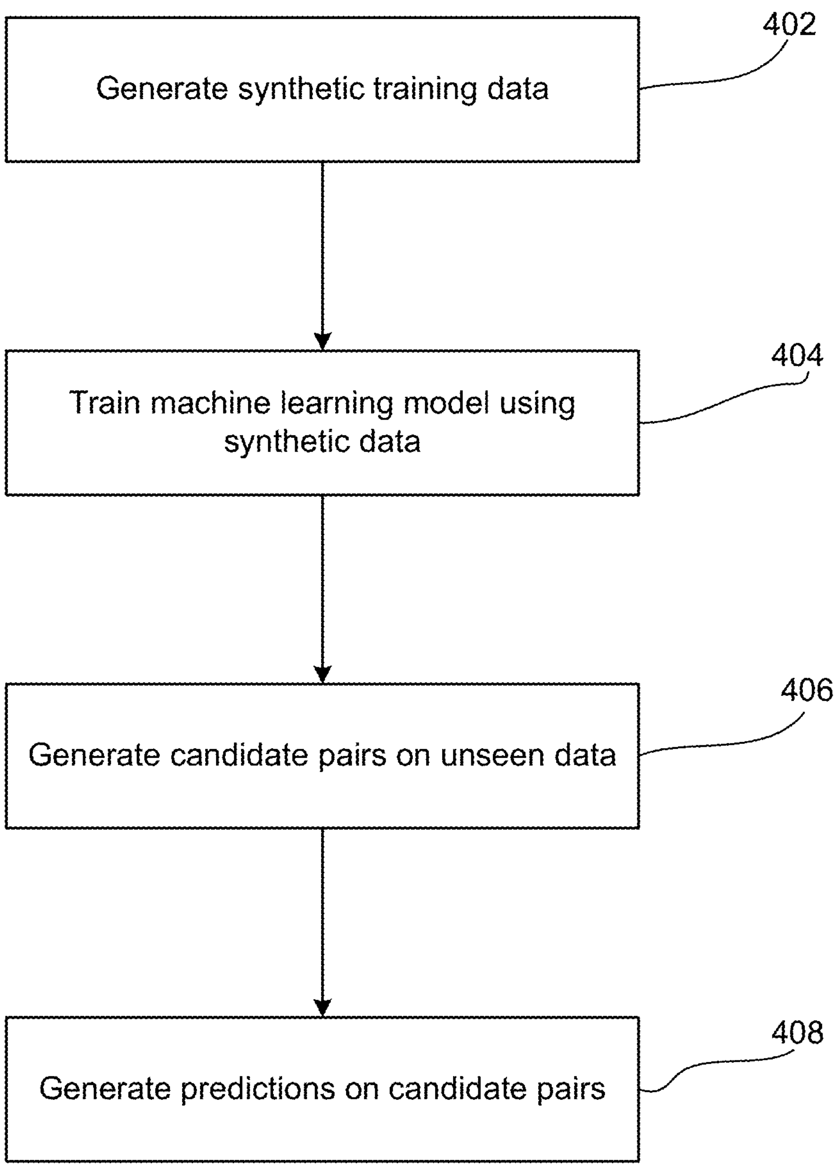

Generate synthetic training data
402
Train machine learning model using synthetic data
404
Generate candidate pairs on unseen data
406
Generate predictions on candidate pairs
408

Fig. 4

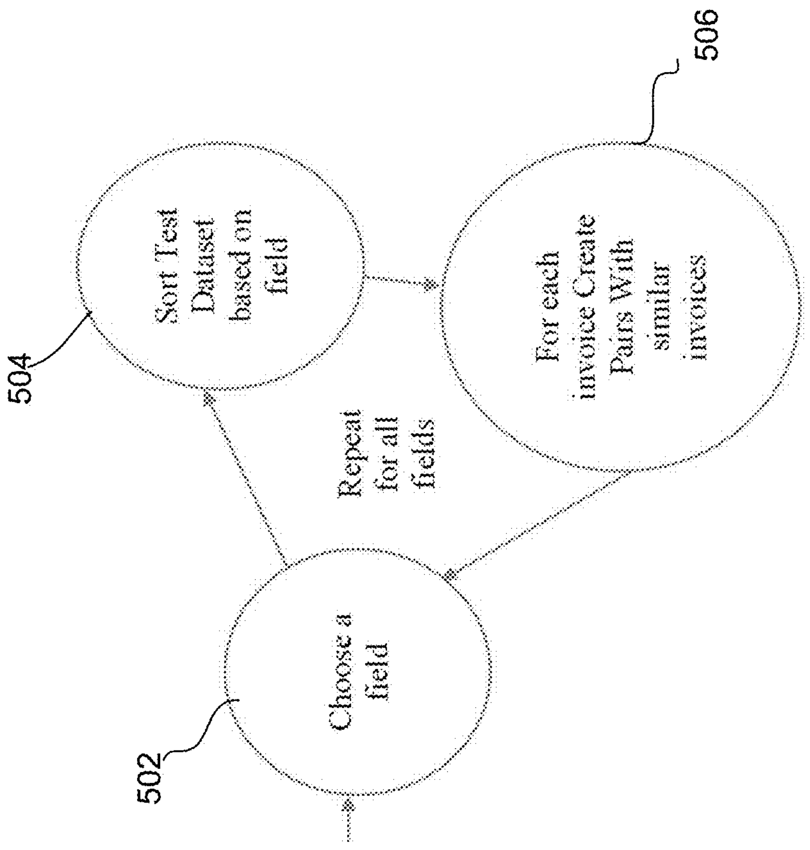
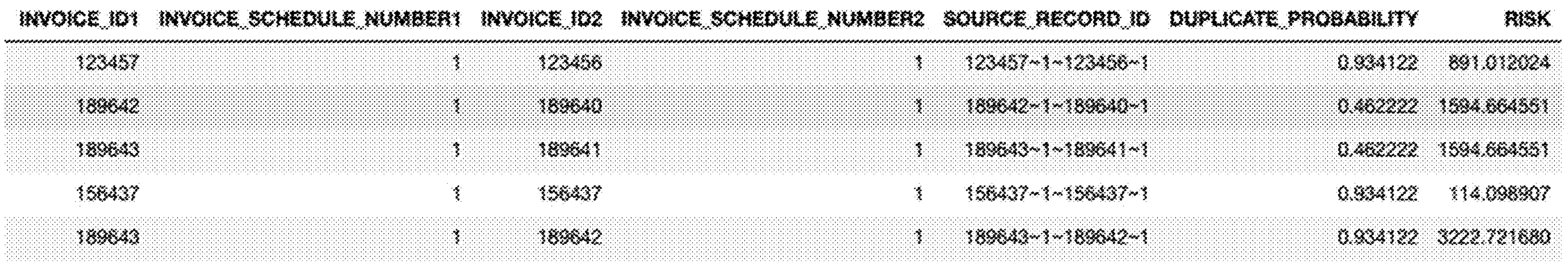

502
Choose a field
504
Sort Test Dataset based on field
506
For each invoice Create Pairs With similar invoices
Repeat for all fields

Fig. 5



INVOICE_ID1	INVOICE_SCHEDULE_NUMBER1	INVOICE_ID2	INVOICE_SCHEDULE_NUMBER2	SOURCE_RECORD_ID	DUPLICATE_PROBABILITY	RISK
123457	1	123456	1	123457~1~123456~1	0.934122	891.012024
189642	1	189640	1	189642~1~189640~1	0.462222	1594.664551
189643	1	189641	1	189643~1~189641~1	0.462222	1594.664551
156437	1	156437	1	156437~1~156437~1	0.934122	114.098907
189643	1	189642	1	189643~1~189642~1	0.934122	3222.721680

Fig. 6

MACHINE LEARNING BASED DUPLICATE INVOICE DETECTION

FIELD

[0001] One embodiment is directed generally to a computer system, and in particular to duplicate invoice detection using a computer system.

BACKGROUND INFORMATION

[0002] Duplicate invoices are received when multiple unneeded invoices with slightly different values (invoice numbers, dates, and sometimes amounts) are produced for the same goods or services. Generally, accounts payable teams have difficulty handling the duplicate invoices. There are several reasons accounts payable teams end up receiving duplicate invoices, including optical character recognition (“OCR”) errors, the same invoice sent multiple time due to late payments, typing errors while entering invoices into a database, and the propensity for vendors to send invoices using multiple channels such as emails, online portals, hardcopies, etc. Organizations can suffer huge financial losses due to paying same invoice multiple times. In addition, the costs and efforts required to manually find duplicate invoices can be very high.

SUMMARY

[0003] Embodiments detect duplicate invoices, each invoice including a plurality of fields. Embodiments generate synthetic training data using a plurality of training invoices and generating one or more modified fields for each of the plurality of training invoices. Embodiments train a machine learning model using the synthetic training data and generate a plurality of candidate invoice pairs. Embodiments input the plurality of candidate invoice pairs to the trained machine learning model and generate, by the trained machine learning model, a prediction of whether each of the candidate invoices pairs is a duplicate invoice pair.

BRIEF DESCRIPTION OF THE DRAWINGS

[0004] Further embodiments, details, advantages, and modifications will become apparent from the following detailed description of the embodiments, which is to be taken in conjunction with the accompanying drawings.

[0005] FIG. **1** illustrates a system for detecting duplicate invoices using machine learning or artificial intelligence according to an example embodiment.

[0006] FIG. **2** is a block diagram of a computer server/system in accordance with an embodiment of the present invention.

[0007] FIG. **3** illustrates an example of invoices that may be identified as possible duplicates.

[0008] FIG. **4** is a flow diagram of the functionality of the duplicate invoice detection module of FIG. **2** for performing duplicate invoice detection in accordance with one embodiment.

[0009] FIG. **5** is a flow diagram to generate an exhaustive list of pairs of invoices which could be duplicates of each other in accordance to embodiments.

[0010] FIG. **6** is an example output showing, for each pair of invoices, the duplicate probability as well as a risk in accordance to embodiments.

DETAILED DESCRIPTION

[0011] One embodiment is a machine learning system that is trained using synthetic data. Candidate pairs of potential duplicate invoices are generated, and the trained machine learning system is used to predict the likelihood that each pair is a duplicate.

[0012] Reference will now be made in detail to the embodiments of the present disclosure, examples of which are illustrated in the accompanying drawings. In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of the present disclosure. However, it will be apparent to one of ordinary skill in the art that the present disclosure may be practiced without these specific details. In other instances, well-known methods, procedures, components, and circuits have not been described in detail so as not to unnecessarily obscure aspects of the embodiments. Wherever possible, like reference numbers will be used for like elements.

[0013] FIG. **1** illustrates a system for detecting duplicate invoices using machine learning (“ML”) or artificial intelligence (“AI”) according to an example embodiment. System **100** includes input data **102**, a processing model **104**, a prediction module **106**, training data **108**, and output data **110**. In some embodiments, input data **102** can include several elements or rows of data, and the data can be processed by processing module **104**. For example, processing module **104** can generate metadata profiles based on input data **102**. In some embodiments, the metadata profiles, not the input data itself, is fed to prediction module **106**.

[0014] In some embodiments, prediction module **106** can be a machine learning model (e.g., neural network, support vector machine (“SVM”), random forests, gradient boosting, etc.) that is trained by training data **108**. For example, training data **108** can include labeled data, such as metadata profiles generated by processing labeled and/or structured data. However, as disclosed below, in embodiments, the training data is synthetic training data, which obviates the need for labeled data. In some embodiments, the output from processing module **104**, such as the processed input data (e.g., metadata profiles), or candidate pairs of invoices, as disclosed below, can be fed as input to prediction module **106**. Prediction model **106** can generate output data **110**, such as a listing of predicted duplicate invoices, in response to input data **102**.

[0015] FIG. **2** is a block diagram of a computer server/system **10** in accordance with an embodiment of the present invention. Although shown as a single system, the functionality of system **10** can be implemented as a distributed system. Further, the functionality disclosed herein can be implemented on separate servers or devices that may be coupled together over a network. Further, one or more components of system **10** may not be included. System **10** can centrally provide the functionality for all or some of the components shown in FIG. **1**.

[0016] System **10** includes a bus **12** or other communication mechanism for communicating information, and a processor **22** coupled to bus **12** for processing information. Processor **22** may be any type of general or specific purpose processor. System **10** further includes a memory **14** for storing information and instructions to be executed by processor **22**. Memory **14** can be comprised of any combination of random access memory (“RAM”), read only memory (“ROM”), static storage such as a magnetic or optical disk, or any other type of computer readable media.

System **10** further includes a communication device **20**, such as a network interface card, to provide access to a network. Therefore, a user may interface with system **10** directly, or remotely through a network, or any other method.

[0017] Computer readable media may be any available media that can be accessed by processor **22** and includes both volatile and nonvolatile media, removable and non-removable media, and communication media. Communication media may include computer readable instructions, data structures, program modules, or other data in a modulated data signal such as a carrier wave or other transport mechanism, and includes any information delivery media.

[0018] Processor **22** is further coupled via bus **12** to a display **24**, such as a Liquid Crystal Display ("LCD"). A keyboard **26** and a cursor control device **28**, such as a computer mouse, are further coupled to bus **12** to enable a user to interface with system **10**.

[0019] In one embodiment, memory **14** stores software modules that provide functionality when executed by processor **22**. The modules include an operating system **15** that provides operating system functionality for system **10**. The modules further include a duplicate invoice detection module **16** that provides ML based duplicate invoice detection, and all other functionality disclosed herein. System **10** can be part of a larger system. Therefore, system **10** can include one or more additional functional modules **18** to include the additional functionality, such as "Fusion Procurement" from Oracle Corp. or an enterprise resource planning ("ERP") system that includes an accounts payable function. A database **17** is coupled to bus **12** to provide centralized storage for modules **16** and **18** and store customer data, product data, transactional data, etc. In one embodiment, database **17** is a relational database management system ("RDBMS") that can use Structured Query Language ("SQL") to manage the stored data.

[0020] In one embodiment, system **10** is a computing/data processing system including an application or collection of distributed applications for enterprise organizations, and may also implement logistics, manufacturing, and inventory management functionality. The applications and computing system **10** may be configured to operate locally or be implemented as a cloud-based networking system, for example in an infrastructure-as-a-service ("IAAS"), platform-as-a-service ("PAAS"), or software-as-a-service ("SAAS") architecture.

[0021] As disclosed, a duplicate invoice may be entered into an Accounts Payable system for multiple reasons. The same invoices may be sent more than once by a vendor for processing due to a delayed payment to the vendor. The same invoices may be sent through multiple channels by vendors (e.g., email, online portals, etc.). There may be OCR errors, such as an 'O' replaced by a '0' or '1' replaced by a pipe (I). Unintentional typographical errors may be made in the course of entering hundreds of invoices per day. Further, fraudulent activities by a vendor may occur such as trying to claim reimbursements multiple times by sending the same invoice multiple times and hoping the payee does not detect the duplicate invoices.

[0022] Duplicate invoices are generally difficult to handle by enterprise Accounts Payable teams because of the potentially substantial manual requirements. The risk that an Accounts Payable team can end up paying an invoice multiple times to its supplier. De-duplicating invoices is very difficult to do manually because a variety of field types make up an invoice (e.g., dates, numbers, currency, text fields, etc.). Due to large volumes, it is infeasible to manually check every invoice as to whether it has already been paid. Most companies resort to checking for duplicate invoice identifiers ("IDs") or use simple rules to identify duplicates.

[0023] FIG. **3** illustrates an example of invoices that may be identified as possible duplicates. Invoices identified by Index **1** and **3** (column **301**) have similar invoice numbers (column **302**), the same supplier (column **303**), similar invoice descriptions (column **304**), a different invoice date (column **305**), and the same amount (column **306**). It would be beneficial for an automated system to detect these pair of invoices, out of thousands or millions of invoices, and provide a prediction of the likelihood that the pair are indeed duplicates.

[0024] Therefore, there is a need for an improved duplicate invoice detection system to avoid large financial losses occurring due to duplicate payments as well as to avoid the cost and manual effort required to review the invoices to find duplicates

[0025] Automated duplicate detection solutions are difficult to implement because of the unavailability of data of all different types of possible duplicates. Further, it is generally infeasible to compare each invoice with every other invoice available in a database, assuming a large organization, so there is a need to reduce the search space.

[0026] In contrast to known solutions, embodiments train a machine learning model on a synthetic training dataset and use this model to make predictions (duplicate/non-duplicate) on "unseen" data (i.e., new incoming data or data which the ML model has not seen during the training phase).

[0027] FIG. **4** is a flow diagram of the functionality of duplicate invoice detection module **16** of FIG. **2** for performing duplicate invoice detection in accordance with one embodiment. In one embodiment, the functionality of the flow diagram of FIG. **4** (and FIG. **5** below) is implemented by software stored in memory or other computer readable or tangible medium, and executed by a processor. In other embodiments, the functionality may be performed by hardware (e.g., through the use of an application specific integrated circuit ("ASIC"), a programmable gate array ("PGA"), a field programmable gate array ("FPGA"), etc.), or any combination of hardware and software.

[0028] Embodiments utilize invoices having one or more of the fields/columns shown in Table 1 below. In other embodiments, a different combination of fields can be used. In embodiments, the fields can be stored in a database as a specialized data structure as a database table.

TABLE 1

	Field/column name	Description
1	Invoice_ID	Invoice ID
2	Invoiced_On_Date	Date on which invoice is created
3	Invoice_Schedule_Due_Date	Invoice due date
4	Invoice_Amount	Invoice amount
5	Vendor_ID	Vendor ID
6	Vendor_Account_Number	Vendor account number
7	Invoice_Description	Text description on invoice
8	Invoice_Created_By_UserID	User who has created the invoice

[0029] At **402**, synthetic training data is generated. In order to train an accurate machine learning system, embodiments need to include as many as possible types of duplicates as part of the training data. However, many organizations do not this data readily available. Therefore, embodiments create a synthetic training dataset covering all, or practically all, different possible types of invoice duplicates.

[0030] Embodiments begin with an initial dataset of "k" original invoices, where k in embodiments includes approximately 500-2000 invoices, depending upon availability of data. The initial dataset should not include any duplicate invoices. In embodiments, the training invoices of the initial dataset are selected which have as much as possible different values for each field, and manual or automated processes can be used to determine that there are no duplicates in the initial dataset. Embodiments select each invoice from the initial dataset and create a duplicate by modifying random number of columns/fields of Table 1 on each invoice. As a result, the synthetic training dataset includes k "duplicate" pairs (i.e., two invoices that are considered duplicate but have some intentionally created differences in one or more fields).

[0031] In embodiments of Table 1, there are 8 fields/columns for each invoice. A duplicate invoice can have any number of fields modified, from **1** to **8**. However, according to the problem definition, most duplicate invoices will have very few unmatching fields since duplicates typically arise from sources such as OCR errors, typing errors, the same invoice sent multiple times, etc. Further, detecting invoices which have very high number of fields modified fraudulently is generally considered a different problem from the duplicate invoice problem, and can be referred to as a "fraud" detection problem. A fraud detection problem can be caused by vendors trying to claim a payment multiple times by modifying the invoice details fraudulently, whereas duplicate invoices arise due to "innocent" mistakes such as disclosed above, which generally result in at least one field of a duplicate invoice that exactly matches with the field of the original invoice. Embodiments disclosed herein generally solve the duplicate invoice problem but are not designed to solve a fraud detection problem.

[0032] With duplicate invoices, the probability of having a lesser number of unmatching fields in a duplicate invoice is higher than the probability of having a higher number of unmatching fields in a duplicate invoice. Therefore, with embodiments, while generating synthetic training data, the distribution of the number of modified fields among the duplicate pairs generated is such that the percentage of pairs with lesser unmatching columns should be higher than percentage of pairs with higher unmatching fields. An example distribution of the number of modified fields in embodiments is shown in Table 2:

TABLE 2

Number of fields modified of an invoice to create its duplicate	% of duplicate pairs (out of k)
1	30%
2	22%
3	18%
4	10%
5	8%
6	6%
7	3%
8	2%

[0033] The above distribution ensures that the synthetic training data will have higher duplicate pairs with a lesser number of unmatching fields, and lesser duplicate pairs with a higher number of unmatching fields. The percentage numbers in Table 2 can differ in other embodiments.

[0034] Embodiments modify different fields using different operations, depending on their datatypes. Table 3 below provides details on how each field of Table 1 is modified in accordance to embodiments:

TABLE 3

Field Name	Method to modify
1. Invoice_ID	Edit distance operation (randomly choose to insert/delete/replace character at random index)
2. Invoiced_On_Date	Randomly add days or months or years to existing date
3. Invoice_Schedule_Due_Date	Randomly add days or months or years to existing date
4. Invoice_Amount	1. Round off 2. Consider up to 2 digits after decimal 3. Add random integer {1, −1} 4. Edit distance operation after decimal point
5. Vendor_ID	Edit distance operation (randomly choose to insert/delete/replace character at random index)
6. Vendor_Account_Number	Edit distance operation (randomly choose to insert/delete/replace character at random index)
7. Invoice_Description	1. Edit distance operation (randomly choose to insert/delete/replace character at random index) 2. Adding word synonyms using off the self nlp wordnet library or using embedding
8. Invoice_Created_By_UserID	Edit distance operation (randomly choose to insert/delete/replace character at random index)

[0035] The functionality of **402** generates k duplicate pairs. Next, embodiments generate non-duplicate pairs using the initial dataset with k original invoices by pairing each original invoice with other non-duplicate (k-1) original invoices. The synthetic labeled training data is formed by combining the generated duplicate and non-duplicate pairs, with each pair labeled either duplicate or non-duplicate.

[0036] While choosing the initial data of original invoices, embodiments include invoices from multiple organizations. Including a variety of invoices in training data will help to create a more robust machine learning model for duplicate detection.

[0037] Table 4 below provide examples of duplicate invoices generated using **402** of FIG. **4**. Rows with the same number in the far right column are considered a pair of duplicate invoices, where one or more fields differ.

TABLE 4

Invoice_ID	Invoiced_On_Date	Invoice_Schedule_Due_Date	Invoice_Amount	Vendor_ID	Vendor_Account_Number
32L3z73xh	2002 Aug. 4	2002 Sep. 18	4689.9702	12444	2332
32373	2002 Aug. 4	2002 Sep. 18	4689.9702	12444	2332
202587	2014 Jan. 6	2014 Jan. 6	1500	g0010Df32575IU8	03JL2575Hm7b07
202587	2014 Jan. 6	2014 Jan. 6	1500	300100032575688	032575707
9w112V0	2013 Sep. 16	2013 Dec. 9	78259.978	300100027268054	300100027268072
191200	2013 Sep. 10	2013 Dec. 9	78257.77922	300100027268054	300100027268072
248112	2008 Nov. 19	2006 Dec. 20	3295.02	100000011592689	100000011592736c
248112	2006 Nov. 20	2006 Nov. 20	3295.019157	100000011592689	100000011592736
183N44	2013 Aug. 21	2013 Aug. 20	100.8	6595597	11775
183744	2013 Aug. 20	2013 Aug. 20	100	6595597	11775
1642656	2010 Oct. 13	2012 Apr. 25	131.27	5V64	d99999
164265	2009 Oct. 13	2012 Apr. 25	131.27	5264	−99999
514117	2009 Dec. 16	2009 Dec. 13	100	659U5597	1775
5141173	2009 Dec. 14	2009 Dec. 14	101	6595597	11775
372249e	2018 Oct. 19	2020 Nov. 17	1138	30010003257578	300100M36117600
372249	2018 Nov. 18	2018 Nov. 18	1138.20032	300100032575708	300100136117600

Invoice_ID	Invoice_Description	Invoice_Created_By_UserID	n_fields_modified
32L3z73xh	Misc.	2046	1
32373	Misc.	2046	1
202587	Misc.	OPERATIONS	2
202587	Misc.	OPERATIONS	2
9w112V0	Misc.	CVBUYER01	3
191200	Misc.	CVBUYER01	3
248112	Misc.	PV_ITALY	4
248112	Misc.	PV_ITALY	4
183N44	abcdefg	0g	5
183744	ABCD	0	5
1642656	Test9.4	OPERATIONS	6
164265	Test9.5	OPERATION	6
514117	xyz	OPERATIONS	7
5141173	wxyz	OPERATIONS	7
372249e	abcd	AP_SUPV_Pp	8
372249	ABCD	AP_SUPV_PD	8

[0038] At **404**, the machine learning model is trained using the synthetic dataset of **402** of pairs of invoices, some labeled duplicate and some labeled non-duplicate. Embodiments have a target variable of "Is_Duplicate" (1 indicates Duplicate and 0 indicates non-Duplicate). For training the machine learning model, embodiments create features based on edit distance, numerical difference between fields, number of matching and unmatching fields, Boolean flags on field equality, probability of being duplicates based on number of equal fields, etc. In embodiments the machine learning model is a Gradient Boosting model/classifier that is trained on the synthetic data where the target variable is the Is_Duplicate flag and the input features as listed below. Embodiments then use this trained model to make predictions on unseen data.

[0039] Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees. When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees and typically outperforms random forest. A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

[0040] Table 5 below lists the features used in the Gradient Boosting model in accordance to embodiments.

TABLE 5

	Name of Feature	Description
1	invoice_id_edit_distance	Edit distance between invoice ids of two invoices in the pair

TABLE 5-continued

	Name of Feature	Description
2	vendor_id_edit_distance	Edit distance between vendor ids of two invoices in the pair
3	vendor_account_id_edit_distance	Edit distance between vendor account numbers of two invoices in the pair
4	invoice_amount_diff	Absolute difference between invoice amounts of invoices in the pair
5	user_id_edit_distance	Edit distance between two user ids in the pair
6	on_date_diff_days	Number of days between two invoice creation dates
7	due_date_diff_days	Number of days between two invoice due dates
8	description_similarity	Edit distance between invoice descriptions of two invoices in the pair
9	same_invoice_id	Flag on invoice id equality
10	same_vendor_id	Flag on vendor id equality
11	same_vendor_account_number	Flag on vendor account number equality
12	same_invoice_amount	Flag on invoice amount equality
13	same_user_id	Flag on user id equality
14	same_on_date	Flag on invoice creation dates equality
15	same_due_date	Flag on invoice due dates equality
16	same_description	Flag on invoice description equality
17	n_equal_columns	Total number of fields with equal values in both invoices in the pair
18	n_unequal_columns	Total number of fields with unequal values in both invoices in the pair

[0041] At **406**, embodiments generate candidate pairs of invoices which are suspected duplicates in unseen data, or a "test" set or "live" dataset. To detect duplicate invoices among an unseen data set of n invoices, embodiments first need to create pairs. A brute force approach is to create N(N−1)/2 unique pairs, and check if invoices forming each pair are duplicates of each other or not. However, this solution is infeasible computationally for a large number of invoices (e.g., over 1 million). Therefore, instead, embodiments use the functionality of FIG. **5** to generate an exhaustive list of pairs of invoices which could be duplicates of each other. The functionality of FIG. **5** is a "Blocking" strategy to reduce dimensionality. Each duplicate pair of invoices will have some fields in common, and invoices are grouped by common fields.

[0042] At **502**, one of the fields is chosen. For example, initially the invoice ID field is chosen. At **504**, the live dataset is sorted based in the chosen field. Sorting based on invoice IDs (or other chosen field) will ensure that invoices with equal or similar invoice IDs are ordered close to each other. Sorting has the potential to bring strings with little difference close to each other.

[0043] Now for an invoice with row ID $i \in [0, n-1]$ in the sorted live dataset, at **506** embodiments compare its invoice ID with the invoice ID of the invoice at row id $j=i+1$, $i+2$, $i+3$, . . . and so on, where n is the total number of invoices in the live dataset. Embodiments keep forming the pairs for the invoice at row i with the invoice at row j until the invoice IDs of row i and row j have edit distance less than a predefined threshold.

[0044] Once the edit distance between the invoice IDs of row i and row j is more than the predefined threshold, embodiments stop forming pairs for row i and start forming pairs for the next invoice at row ID i+1. The threshold in embodiments may be a number of rows, a similarity measure, or a combination of both.

[0045] Once the iteration is complete, this process is repeated by sorting on other fields/columns one by one until the sorting is performed on all fields (e.g., 8 fields in embodiments disclosed above). As embodiments are generating pairs by sorting on all columns one by one, some duplicate pairs can be generated. The duplicate pairs will be dropped.

[0046] The total number of pairs generated using the functionality of FIG. **5** is O(n) (i.e., using the "Big O" notation). The overall time complexity is O(nlogn) as there is a need to sort the dataframe.

[0047] Even if two invoices have only a single field with matching values, embodiments ensure that a pair will be formed with them and passed to the classifier for a prediction. This also means that potential duplicate candidate pairs are not being missed.

[0048] The following pseudocode implements the functionality of FIG. **5** to generate candidate pairs:

```
list__of__fields = list with 8 fields of invoices as per table 1
for field__name in list__of__fields
  {
    df = df.sort(columns = ['field__name']) # sort the data-frame based on field__name
    for (i = 0, i<= n−1, i++)
      {
        for (j = i+1, j<= n−1, j++)
          {
             row__i__field = df['field__name'][i]
             row__j__field = df['field__name'][j]
          if( edit__distance(row__i__field, row__j__field) < threshold)
              {
                create__pair(row[i],row[j])
              }
          else
              {
                  break
              }
          }
      }
}
```

[0049] In one embodiment, in addition to generating the candidate pairs at **406**, m invoices are randomly selected. For each of these randomly selected m invoices, embodiments create candidate pairs by forming a pair with another randomly selected n invoice, where m and n are constant numbers. This random sampling can form candidate pairs which may have been missed at **406**.

[0050] At **408**, the candidate pairs generated on the test dataset at **406** are passed through the model trained on the synthetic data (i.e., input to the trained model), and the resulting output will be the predictions duplicate/non-duplicate with a probability score of being duplicate. FIG. **6** is an example output showing, for each pair of invoices, the duplicate probability as well as a risk in accordance to embodiments. In one embodiment, Risk=(probability of being duplicates)×(max(Invoice Amount of Invoice 1, Invoice Amount of Invoice 2)).

[0051] In one embodiment, the predictions are manually reviewed to determine if the predictions are accurate. The result of the review is labelled data that can be added to the synthetic training data and used to retrain the model at **404**.

[0052] As disclosed, embodiments generate synthetic data to train a machine learning model for detecting invoices. Embodiments then generate candidate pairs of invoices that are input the trained model in order to predict if each pair is a duplicate. The candidate pairs is a subset of all potential pairs so that the automated detection is feasible even with a large number of candidate invoices.

[0053] The features, structures, or characteristics of the disclosure described throughout this specification may be combined in any suitable manner in one or more embodiments. For example, the usage of "one embodiment," "some embodiments," "certain embodiment," "certain embodiments," or other similar language, throughout this specification refers to the fact that a particular feature, structure, or characteristic described in connection with the embodiment may be included in at least one embodiment of the present disclosure. Thus, appearances of the phrases "one embodiment," "some embodiments," "a certain embodiment," "certain embodiments," or other similar language, throughout this specification do not necessarily all refer to the same group of embodiments, and the described features, structures, or characteristics may be combined in any suitable manner in one or more embodiments.

[0054] One having ordinary skill in the art will readily understand that the embodiments as discussed above may be practiced with steps in a different order, and/or with elements in configurations that are different than those which are disclosed. Therefore, although this disclosure considers the outlined embodiments, it would be apparent to those of skill in the art that certain modifications, variations, and alternative constructions would be apparent, while remaining within the spirit and scope of this disclosure. In order to determine the metes and bounds of the disclosure, therefore, reference should be made to the appended claims.

What is claimed is:

1. A method of detecting duplicate invoices, each invoice comprising a plurality of fields, the method comprising:

generating synthetic training data using a plurality of training invoices and generating one or more modified fields for each of the plurality of training invoices;

training a machine learning model using the synthetic training data;

generating a plurality of candidate invoice pairs;

inputting the plurality of candidate invoice pairs to the trained machine learning model; and

generating, by the trained machine learning model, a prediction of whether each of the candidate invoices pairs is a duplicate invoice pair.

2. The method of claim **1**, the synthetic training data comprising a plurality of pairs of duplicate pairs, each duplicate pair comprising a first invoice and a second invoice that is a duplicate of the first invoice and includes one or more modified fields.

3. The method of claim **1**, the synthetic training data comprising a plurality of pairs of non-duplicate pairs comprising pairing each of k training invoices with a k-1 invoice.

4. The method of claim **1**, the generating the plurality of candidate invoice pairs comprises receiving a plurality of unseen invoices and sorting on each field of the unseen invoices to form groups of common field invoices, and determining in each group a pair of invoices having an edit distance less than a predefined threshold.

5. The method of claim **1**, the prediction comprising a duplicate probability and a risk.

6. The method of claim **1**, wherein the machine learning model comprises a gradient boosting model.

7. The method of claim **1**, further comprising:

determining an accuracy of the prediction; and

retraining the machine learning model based on the accuracy.

8. The method of claim **4**, the generating the plurality of candidate invoice pairs further comprising forming a plurality of randomly selected pairs.

9. A computer readable medium having instructions stored thereon that, when executed by one or more processors, cause the processors to detect duplicate invoices, each invoice comprising a plurality of fields, the detecting comprising:

generating synthetic training data using a plurality of training invoices and generating one or more modified fields for each of the plurality of training invoices;

training a machine learning model using the synthetic training data;

generating a plurality of candidate invoice pairs;

inputting the plurality of candidate invoice pairs to the trained machine learning model; and

generating, by the trained machine learning model, a prediction of whether each of the candidate invoices pairs is a duplicate invoice pair.

10. The computer readable medium of claim **9**, the synthetic training data comprising a plurality of pairs of duplicate pairs, each duplicate pair comprising a first invoice and a second invoice that is a duplicate of the first invoice and includes one or more modified fields.

11. The computer readable medium of claim **9**, the synthetic training data comprising a plurality of pairs of non-duplicate pairs comprising pairing each of k training invoices with a k-1 invoice.

12. The computer readable medium of claim **9**, the generating the plurality of candidate invoice pairs comprises receiving a plurality of unseen invoices and sorting on each field of the unseen invoices to form groups of common field invoices, and determining in each group a pair of invoices having an edit distance less than a predefined threshold.

13. The computer readable medium of claim **9**, the prediction comprising a duplicate probability and a risk.

14. The computer readable medium of claim **9**, wherein the machine learning model comprises a gradient boosting model.

15. The computer readable medium of claim **9**, the detecting further comprising:

determining an accuracy of the prediction; and

retraining the machine learning model based on the accuracy.

16. The computer readable medium of claim **12**, the generating the plurality of candidate invoice pairs further comprising forming a plurality of randomly selected pairs.

17. A duplicate invoice detection system comprising:

a database storing a plurality of training invoices; and

one or more processors coupled to the database and configured to detect duplicate invoices, each invoice comprising a plurality of fields, detecting comprising:

generating synthetic training data using the plurality of training invoices and generating one or more modified fields for each of the plurality of training invoices;

training a machine learning model using the synthetic training data;

generating a plurality of candidate invoice pairs;

inputting the plurality of candidate invoice pairs to the trained machine learning model; and

generating, by the trained machine learning model, a prediction of whether each of the candidate invoices pairs is a duplicate invoice pair.

18. The system of claim **17**, the synthetic training data comprising a plurality of pairs of duplicate pairs, each duplicate pair comprising a first invoice and a second invoice that is a duplicate of the first invoice and includes one or more modified fields.

19. The system of claim **17**, the synthetic training data comprising a plurality of pairs of non-duplicate pairs comprising pairing each of k training invoices with a k-1 invoice.

20. The system of claim **17**, the generating the plurality of candidate invoice pairs comprises receiving a plurality of unseen invoices and sorting on each field of the unseen invoices to form groups of common field invoices, and determining in each group a pair of invoices having an edit distance less than a predefined threshold.

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