# Analysis of selected articles

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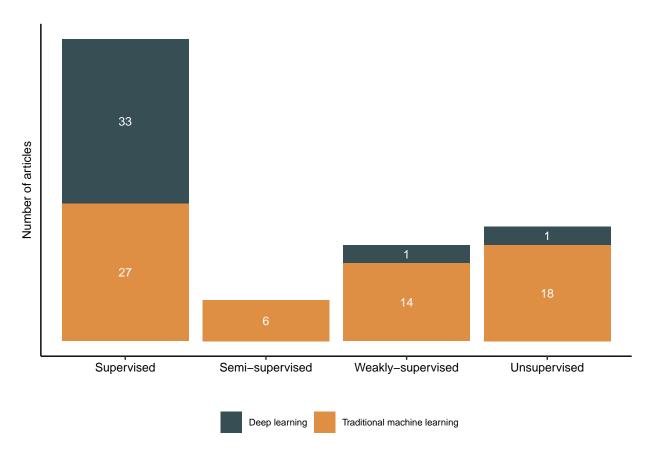
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### Contents

1	Ma	chine learning (ML) methods	2
	1.1	ML paradigms	2
	1.2	Traditional ML methods	2
	1.3	Deep learning (DL) methods	3
2	Phe	enotypes	5
	2.1	Phenotypes considered across ML paradigms	5
	2.2	Unstratified summary of phenotypes considered	6
3	Dat	ta sources	7
	3.1	Use of structured and unstructured data	7
	3.2	Structured and unstructured data types	8
	3.3	Terminologies	9
	3.4	Natural language processing (NLP) software	10
	3.5	Embeddings	10
	3.6	Openly-available data	11
	3.7	Private data sources and demographics reporting	13
	3.8	Institutions	13
	3.9	Data sources summary across different ML paradigms	13
4	Val	idation and comparison	15
	4.1	Traditonal supervised ML vs. rule-based	15
	4.2	Deep supervised ML vs. traditional supervised ML	16
5	Mo	del performance metric reporting	17

## 1 Machine learning (ML) methods

### 1.1 ML paradigms



### 1.2 Traditional ML methods

Table 1: Common traditional machine learning methods (Count > 1)

ML	Traditional ML method	Count
Supervised	Random forest	14
Supervised	Logistic regression	11
Supervised	SVM	11
Supervised	L1 logistic regression	8
Supervised	Decision trees	4
Supervised	XGBoost	4
Supervised	Naive Bayes	3
Weakly-supervised	PheNorm	3
Weakly-supervised	MAP	2
Weakly-supervised	Random forest	2
Unsupervised	LDA	5
Unsupervised	K-means	4
Unsupervised	UPGMA Hierarchical clustering	2

## [1] "There are 18 papers using multiple traditional machine learning methods"

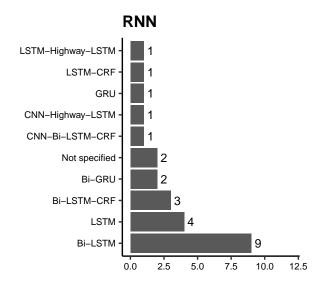
## $1.3\quad \text{Deep learning (DL) methods}$

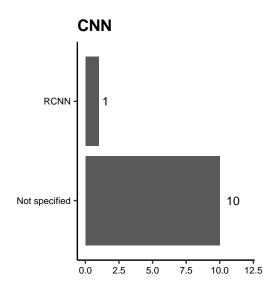
Table 2: Common deep learning methods (Count > 1)

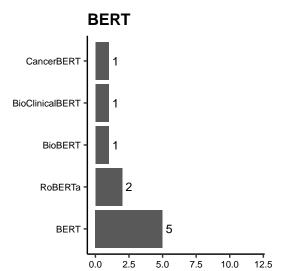
DL method	ML	Count
BERT	Supervised	7
CNN	Supervised	11
FFNN	Supervised	3
RNN	Supervised	19

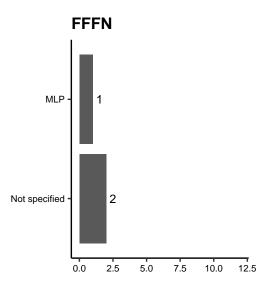
## [1] "There are 5 papers using multiple deep learning methods"

#### 1.3.1 Neural network variants



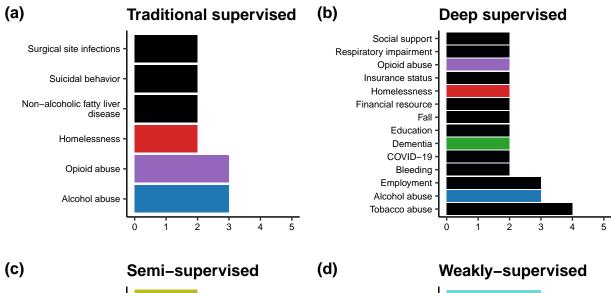


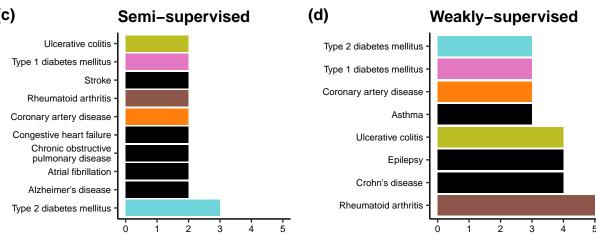


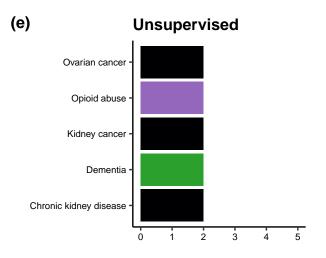


### 2 Phenotypes

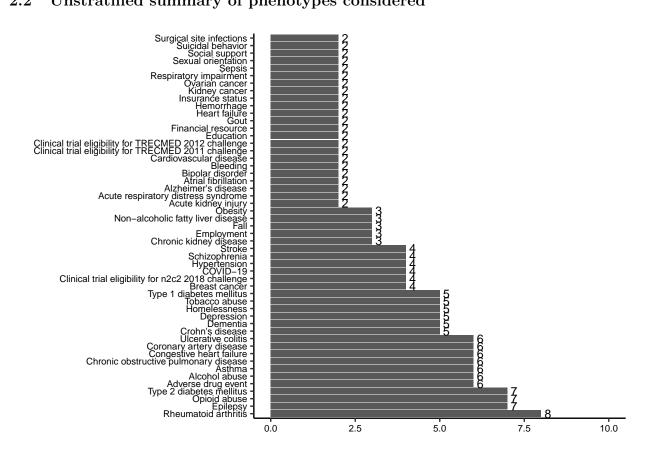
#### 2.1 Phenotypes considered across ML paradigms







### 2.2 Unstratified summary of phenotypes considered



### 3 Data sources

### 3.1 Use of structured and unstructured data

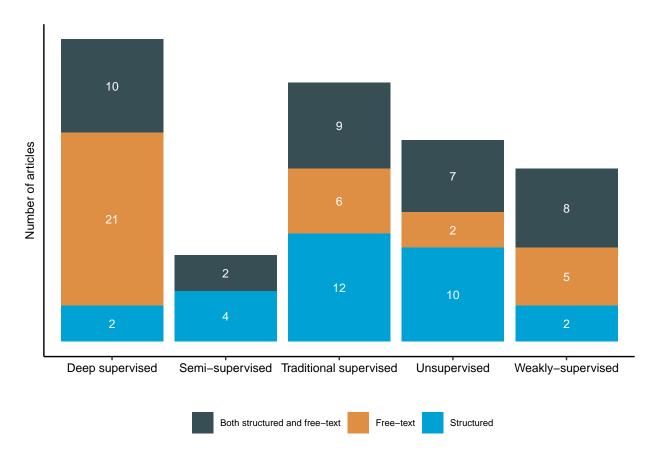
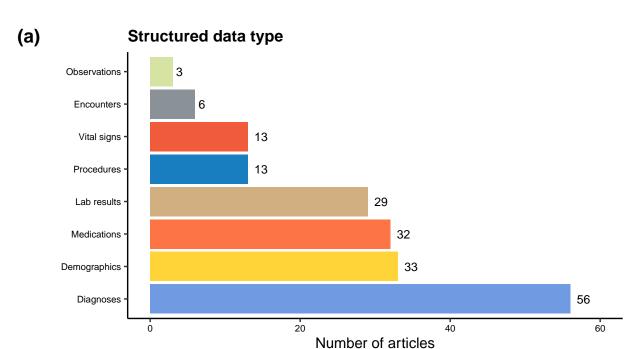


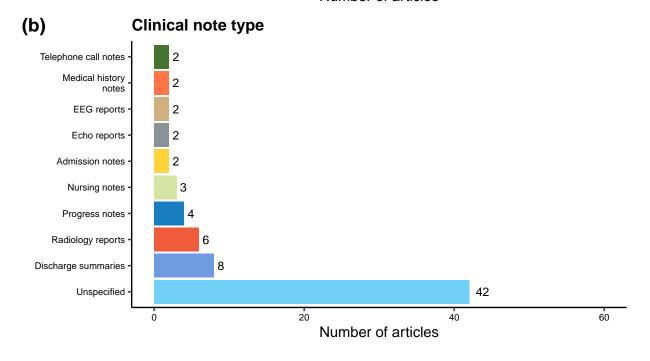
Table 3: Use of structured and unstructured data

Data	Count
Both structured and free-text	36
Free-text	34
Structured	30

### 3.2 Structured and unstructured data types

- ## [1] "There are 50 papers using multiple structured data types"
- ## [1] "There are 13 papers using multiple unstructured data types"





Terminology unnested	Supervised Traditional machine learning	Unsupervised Traditional machine learning	Supervised Deep learning	Weakly- supervised Traditional machine learning	Semisupervised Traditional machine learning	Count
ICD-9	18	8	7	5	4	42
UMLS	11	3	8	8	1	31
ICD-10	11	2	4	1	3	21
SNOMED- CT	2	3	4	3	0	12
RxNorm	3	1	2	2	1	9
CPT	2	0	3	2	0	7
Phecode	0	2	0	3	2	7
ICD	0	1	0	4	0	5
LOINC	3	0	0	1	0	4
ATC (Anatomical therapeutic chemical)	2	0	0	0	0	2
NDC (National drug codes)	2	0	0	0	0	2

## 3.3 Terminologies

## [1] "There are 43 papers using multiple terminologies"

NLP software	Supervised Deep learning	Weakly- supervised Traditional machine learning	Supervised Traditional machine learning	Semisupervised Traditional machine learning	Unsupervised Traditional machine learning	Count
cTAKES NegEx NILE NLTK MetaMap	8 0 0 4 1	0 2 5 0	8 3 1 0 3	1 0 0 0 0	2 1 0 1 0	19 6 6 5 4
Stanford CoreNLP	2	0	0	0	0	2

### 3.4 Natural language processing (NLP) software

## [1] "There are 7 papers using multiple NLP software"

### 3.5 Embeddings

Embeddings were only used in deep supervised articles.

Embedding training data	Count
Unstructured EHR	11
Biomedical literature	10
MIMIC-III database (internal)	7
MIMIC-III database (external)	6
Wikipedia	6
Structured EHR	2

## [1] "There are 7 papers using multiple embedding training data"

Embedding	Count
Word2vec	19
GloVe BERT	6 5
RoBERTa	3
BioBERT BioClinicalBERT	$\frac{2}{2}$
FastText	$\frac{2}{2}$
Not specified	2

## [1] "There are 11 papers using multiple embedding training methods"

## $3.6\quad {\rm Openly\text{-}available\ data}$

### 3.6.1 Competition data

## [1] "There are 2 papers using multiple competition data"

Competition data name	Supervised Traditional machine learning	Supervised Deep learning	Count
2018 n2c2 track 2	0	6	6
2018 n2c2 track 1	1	3	4
TRECMED 2011	1	1	2
TRECMED 2012	1	1	2
2008 i2b2	1	0	1
2012 physionet Challenge	0	1	1

Data source	Supervised Deep learning	Supervised Traditional machine learning	Weakly- supervised Deep learning	Weakly- supervised Traditional machine learning	Unsupervised Traditional machine learning	Count
MIMIC-III database	9	1	1	1	3	15
MTSamples database	1	0	0	0	0	1

### 3.6.2 Other publicly available data sources

### 3.7 Private data sources and demographics reporting

## [1] "71 articles did not use openly available data"

## [1] "Among these 71 articles, 38 articles considered temporal phenotypes"

### 3.8 Institutions

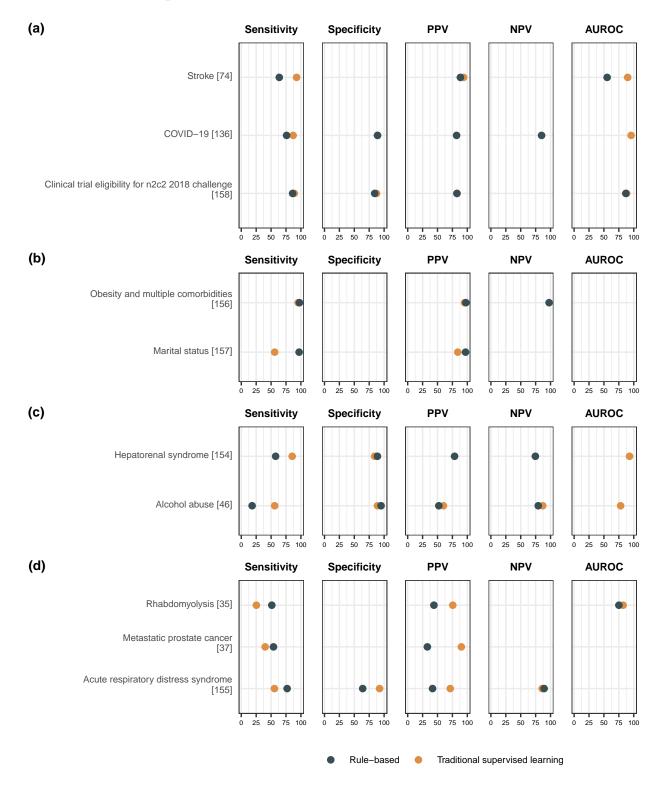
Country	Count
US	94
France	2
Cancada	1
China	1
Germany	1
Israel	1
Italy	1
Korean	1
Netherland	1
Singapore	1
Spain	1

### 3.9 Data sources summary across different ML paradigms

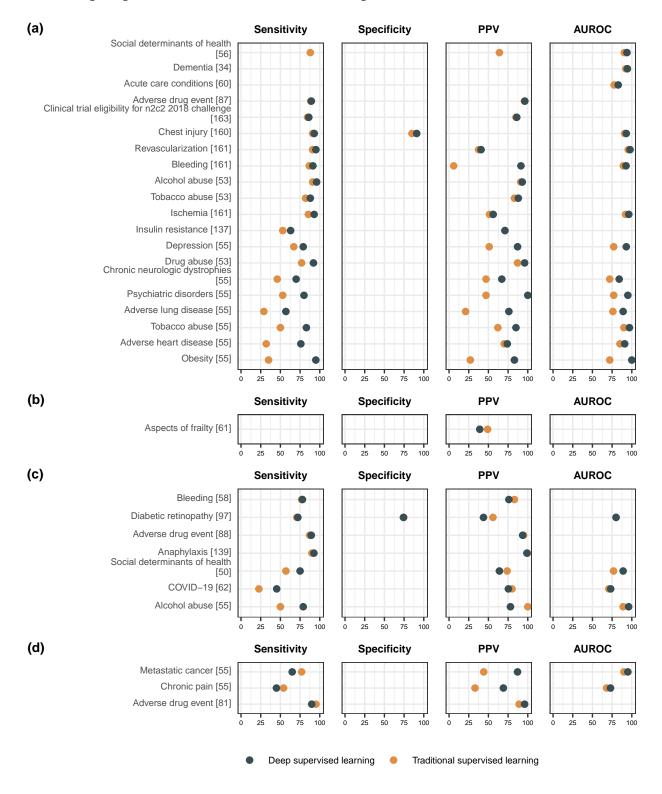
	Total number of papers	Used free-text	Used NLP software	Used competition data	Used multisite data	Used open data	Used private single-site data	Compared to rule-based algo-rithms	Comapred to tradi- tional ML	Reported patient demographic	Released open code
TSL	27	15	14	3	1	1	22	10	0	13	4
DSL SSL	33 6	31 2	18 1	11 0	1 0	9	12 6	1	20 0	5 3	9
WSL USL	15 19	13 9	10 4	0	3	$\frac{2}{3}$	10 13	8	0	13	$\frac{3}{4}$
Total	100	70	47	14	8	15	63	21	21	38	20

### 4 Validation and comparison

### 4.1 Traditonal supervised ML vs. rule-based



### 4.2 Deep supervised ML vs. traditional supervised ML



Model	Supervised	Supervised	Weakly-	Weakly-	Semi-	Count
perfor-	Deep	Tradi-	supervised	supervised	supervised	
mance	learning	tional	Deep	Tradi-	Tradi-	
metrics		machine	learning	tional	tional	
		learning		machine	machine	
				learning	learning	
Precision	26	23	0	8	4	61
Recall	25	23	1	7	2	58
AUROC	11	15	1	10	5	42
F-score	26	9	0	7	0	42
Specificity	6	11	1	1	0	19
Accuracy	4	8	1	4	0	17
NPV	1	7	0	5	2	15
AUPRC	4	2	0	2	0	8
Calibration	2	3	0	0	0	5
plots						
Log loss	1	1	0	0	1	3
Brier	1	1	0	0	0	2
score						
Hamming	2	0	0	0	0	2
loss						
Matthews	1	1	0	0	0	2
Correla-						
tion						
Coeffi-						
$\operatorname{cient}$						
Normalized	1	1	0	0	0	2
dis-						
counted						
cumula-						
tive gain						

# 5 Model performance metric reporting