Review Article
Can Artificial Intelligence Be Applied to Diagnose Intracerebral Hemorrhage under the Background of the Fourth Industrial Revolution? A Novel Systemic Review and Meta-Analysis

Kai Zhao,1 Qing Zhao,2 Ping Zhou,3 Bin Liu,3 Qiang Zhang4,3 and Mingfei Yang4,3

1Graduate School, Qinghai University, Xining 810016, Qinghai, China
2Human Resource, Women's and Children's Hospital of Qinghai Province, Xining 810007, Qinghai, China
3Department of Neurosurgery, Qinghai Provincial People's Hospital, Xining 810007, Qinghai, China

Correspondence should be addressed to Qiang Zhang; zhangqiang691212@163.com

Received 10 November 2021; Accepted 24 January 2022; Published 24 February 2022

Academic Editor: Ahmad Mansour

Copyright © 2022 Kai Zhao et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Aim. We intended to provide the clinical evidence that artificial intelligence (AI) could be used to assist doctors in the diagnosis of intracerebral hemorrhage (ICH). Methods. Studies published in 2021 were identified after the literature search of PubMed, Embase, and Cochrane. Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) was used to perform the quality assessment of studies. Data extraction of diagnosis effect included accuracy (ACC), sensitivity (SEN), specificity (SPE), positive predictive value (PPV), negative predictive value (NPV), area under curve (AUC), and Dice scores (Dices). The pooled effect with its 95% confidence interval (95% CI) was calculated by the random effects model. I-Square (I²) was used to test heterogeneity. To check the stability of the overall results, sensitivity analysis was conducted by recalculating the pooled effect of the remaining studies after omitting the study with the highest quality or the random effects model was switched to the fixed effects model. Funnel plot was used to evaluate publication bias. To reduce heterogeneity, recalculating the pooled effect of the remaining studies after omitting the study with the lowest quality or perform subgroup analysis. Results. Twenty-five diagnostic tests of ICH via AI and doctors with overall high quality were included. Pooled ACC, SEN, SPE, PPV, NPV, AUC, and Dices were 0.88 (0.83–0.93), 0.85 (0.81–0.89), 0.90 (0.88–0.92), 0.80 (0.75–0.85), 0.93 (0.91–0.95), 0.84 (0.80–0.89), and 0.90 (0.85–0.95), respectively. There was no publication bias. All of results were stable as revealed by sensitivity analysis and were accordant as outcomes via subgroups analysis. Conclusion. Under the background of the fourth industrial revolution, AI might be an effective and efficient tool to assist doctors in the clinical diagnosis of ICH.

1. Introduction

Appearance of the fourth industrial revolution was based on the digitization and big data analysis [1]. The typical representatives were artificial intelligence (AI) and blockchain [2]. Without exception, there were more and more AI technologies or various software applied in medicine, especially in medical imageology [3]. Stroke was a major cause of death and disability globally; in particular, hemorrhagic strokes (including intracerebral and subarachnoid hemorrhage) had a relatively stable incidence adjusted for age in high-income countries but an increasing incidence in low-income and middle-income countries each year [4]. Of the approximately 15 million strokes reported worldwide annually, intracerebral hemorrhage (ICH) accounts for approximately 10% to 15% of all stroke cases in the United Statement, Europe, and Australia and approximately 20% to 30% of strokes in Asia [5]. The median 30-day mortality rate after ICH is approximately 15–50%, and only 20% of patients regain functional independence within three months after the ictus [6]. Therefore, ICH, as a stroke subtype with high mortality and poor functional outcome in survivors, needed the accurate and objective evidence of neuroimaging to make a definite diagnosis [7]. AI used to diagnose ICH based on neuroimaging gradually became a trend to promote the development of intelligent medicine and efficiency of
clinch̄ṭersṭy recently [8]. Apart from economic interest and development of AI industries, in the aspect of diagnostics, there was no evidence that AI could assist doctors in practically clinical work. In view of that the development of AI industries was quick as a flash, we intend to perform a novel systemic review and meta-analysis based on recent diagnostic tests, which were able to represent the state of the art AI technologies, to verify the hypothesis that AI might be an effective and efficient tool to diagnose ICH.

2. Materials and Methods

2.1. Search Strategy. Literature search was performed in three public electronic databases of PubMed, Embase and Cochrane. The strategy of literature search was as follows: (((((((((((((Intelligence, Artificial)[Title/Abstract]) OR ("Artificial Intelligence"[Mesh])) OR (Computational Intelligence)[Title/Abstract]) OR (Intelligence, Computational [Title/Abstract]) OR (Machine Intelligence)[Title/Abstract]) OR (Intelligence, Machine)[Title/Abstract]) OR (Computer Reasoning)[Title/Abstract]) OR (Reasoning, Computer)[Title/Abstract]) OR (AI (Artificial Intelligence)[Title/Abstract]) OR (Computer Vision System)[Title/Abstract]) OR (System*, Computer Vision)[Title/Abstract]) OR (Vision System*, Computer)[Title/Abstract]) OR (Knowledge Acquisition (Computer)[Title/Abstract]) OR (Acquisition, Knowledge (Computer)[Title/Abstract]) OR (Knowledge Representation* (Computer)[Title/Abstract]) OR (Representation, Knowledge (Computer)[Title/Abstract]) OR ((("Machine Learning"[Mesh]) OR (Learning, Machine)[Title/Abstract]) OR (Transfer Learning [Title/Abstract]) OR (Learning, Transfer)[Title/Abstract])) AND (((((((("Cerebral Hemorrhage"[Mesh]) OR (Hemorrhage*, Cerebrum)[Title/Abstract]) OR (Cerebrum Hemorrhage)[Title/Abstract]) OR (Cerebral Parenchymal Hemorrhage)[Title/Abstract]) OR (Hemorrhage*, Cerebral Parenchymal)[Title/Abstract]) OR (Parenchymal Hemorrhage*, Cerebral)[Title/Abstract]) OR (Intracerebral Hemorrhage)[Title/Abstract]) OR (Hemorrhage*, Intracerebral)[Title/Abstract]) OR (Hemorrhage*, Cerebral)[Title/Abstract]) OR (Cerebral Hemorrhages)[Title/Abstract]) OR (Brain Hemorrhage*, Cerebral)[Title/Abstract]) OR (Cerebral Brain Hemorrhage)[Title/Abstract]) OR (Hemorrhage*, Cerebral Brain)[Title/Abstract])).

2.2. Inclusion Criteria. (1) Language and regions of articles were not restricted; (2) articles were published in 2021; (3) diagnostic tests; (4) true-positive participates were patients suffered ICH; (5) true-negative participates were people without abnormal condition in neuroimaging; (6) the gold standard was that professional physicians, who were blind to tests, diagnose ICH or no ICH referring to the International Classification of Diseases and recent international standards guidelines; (7) full-automatic or semi-automatic diagnostic conclusions via AI technologies were used to compare with full-manual diagnostic outcomes via professional physician; (8) analysis or assessment of diagnosis effect was performed completely.

2.3. Exclusion Criteria. (1) Duplication; (2) reviews, comments, letters, case reports, protocols of clinic trials, and conference papers; (3) animal experiments; (4) and contents of articles were irrelevant to this meta-analysis.

2.4. Quality Assessment. The quality assessment of the included articles was performed via the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) by the software Review Manager 5.3 before data extraction. We considered that the study might be assessed to have higher quality for its larger number of included patients in studies with the same assessment in QUADAS-2.

2.5. Data Extraction. All the original data used to assess diagnosis effect were extracted including accuracy (ACC), sensitivity (SEN), specificity (SPE), positive predictive value (PPV), negative predictive value (NPV), area under curve (AUC), and Dice scores (Dices). In addition, some confounders, which might result in errors, were adjusted, including different diagnosis purposes, AI technologies, and other factors.

2.6. Statistical Analysis. Relative numbers and their 95% confidence intervals (95%CI) were used to describe count data. Meta-analysis was performed using corresponding modules in Software for Statistics and Data Science (Stata, version 15.1; College Station, Texas 77845 USA). The pooled effect with its 95%CI was calculated by the random effects model. I-Square ($I^2$) was used to test the heterogeneity. Sensitivity analysis was performed to evaluate the stability of overall results by recalculating the pooled effect of the remaining studies after omitting the study with the highest quality or the random effects model was switched to fixed effects model. Funnel plot symmetry and Egger’s regression were used to evaluate publication bias. To reduce heterogeneity, recalculating the pooled effect of the remaining studies after omitting the study with the lowest quality or perform subgroups analysis. All $p$ values were two-sided with a significant level at 0.05.

3. Results

3.1. Literature Search and Study Characteristics. Totally, 142 articles were retrieved from 3 databases according to the strategy. After screening according to the inclusion and exclusion criteria, 25 articles [9–33] of diagnostic tests were enrolled ultimately (Figure 1). A total of 23071 ICH patients participated in all the tests, who were manually diagnosed by professional physicians referring to the gold standard of ICH diagnosis in the latest international clinical guidelines (Table 1). 24 AI technologies or methods based on clinical features and neuroimaging were participate in all the tests. The aims of the tests were classified into 4 main aspects: detection of ICH, segmentation of ICH in neuroimaging, prediction of prognosis, and hematoma enlargement in ICH patients. The conclusion with the same tendency was that AI could effectively assist diagnosis of ICH. Specially, four articles (Lu Li, Yu Lei, Stefan Pszczolkowski, Masahito...
Figure 1: Process of literature search.

Table 1: Characters of studies included (*“*” presented that 2 styles of hematoma volume were studied independently in one study. “ab” presented that 2 solutions of ICH were studied independently in one study. “∗∗” presented that 2 aims were studied independently in one study. “∗∗∗” presented that the same first author performed another study).

| Author            | Application                        | AI                                                                 | ICH patient participation | Conclusion                                                                 |
|-------------------|------------------------------------|-------------------------------------------------------------------|---------------------------|--------------------------------------------------------------------------|
| Ryan A. Rava      | ICH detection                      | Canon’s AUTOStroke solution ICH detection algorithm              | 200                       | It was able to accurately detect ICH                                      |
| Chang Ho Kim      | ICH detection                      | A cascaded deep-learning-based automated segmentation algorithm (CDLA) | 5702                      | It can improve diagnostic accuracy in specific doctor groups              |
| Jeremy J. Heit    | ICH detection                      | RAPID ICH (an automated hybrid 2D-3D convolutional neural network application) | 308                       | It is highly accurate in the detection of ICH and in the volumetric quantification |
| Valeria Abramova  | ICH segmentation                   | A 3D U-net architecture with squeeze-and-excitation blocks       | 76                        | It significantly improved segmentation results                           |
| Nico Buls         | ICH detection                      | Aidoc version 1.3, Tel Aviv, Israel                              | 500                       | It was an adjunct to current real-time radiology workflow                  |
| Lu Li1*           | Big ICH detection and segmentation | U-net-based CNN architectures: convolutional networks for biomedical image segmentation | 130                       | It shows great advantages compared with human experts on hemorrhage lesion diagnosis |
| Lu Li2             | Small ICH detection and segmentation | U-net-based CNN architectures: convolutional networks for biomedical image segmentation | 130                       | It shows great advantages compared with human experts on hemorrhage lesion diagnosis |
| Matthew F. Sharrock | ICH segmentation                  | DeepBleed                                                        | 500                       | It can be incorporated into the workflow of an ICH clinical trial series  |
| Ruijuan Chen      | ICH detection                      | Restricted Boltzmann machine, deep belief network, stacked autoencoder, and denoising autoencoder | 590                       | It can effectively improve the reconstruction accuracy and prediction speed of the image |
| Daniel Ginat      | ICH detection                      | Aidoc (Tel Aviv, Israel)                                         | 1829                      | It is associated with a significantly shorter scan view delay             |
| Suting Zhong      | ICH prediction                     | A backbone neural network MF (multifeatures)—dense net            | 34                        | The improved method can effectively improve the monitoring performance    |
Katsuki) included two independent data extraction. Lu Li’s study separated hematoma volume to “big” and “small” groups to study independently. Yu Lei’s study studied the risk of ICH and occurrence of ICH independently. Stefan Pszczolkowski’ study had two study aims independently: detection of ICH and prediction of prognosis in ICH patients. Masahito Katsuki wrote 2 different articles as the same first author.

### 3.2. Quality Assessment of Studies

The assessment of article quality via QUADAS-2 is shown in Figure 2. In the Risk of Bias section, four studies (Lu Li, Suting Zhong, Valeria Abramova, Yoshiyuki Watanabe) were evaluated as high risk and five studies (Chang Ho Kim, Jeremy J. Heit, Ryan A. Rava, Ruijuan Chen, Daniel Ginat) were evaluated as unclear risk in the Patient Selection segment, and in addition, three studies (Chang Ho Kim, Jeremy J. Heit, Ryan A. Rava) were assessed to...
unclear risk in other segments. In the Applicability Concerns section, four studies (Lu Li, Suting Zhong, Valeriia Abramova, Yoshiyuki Watanabe) were evaluated as high concern and three studies (Chang Ho Kim, Jeremy J. Heit, Ryan A. Rava) were evaluated as unclear concern in the Patient Selection segment, and in addition, three studies (Chang Ho Kim, Jeremy J. Heit, Ryan A. Rava) were assessed to unclear risk in other segments. Except outcomes of the assessment above, any segment was assessed to low risks in the Risk of Bias section or low concerns in the Applicability Concerns section as well as other studies.

3.3. Data Analysis. Total pooled ACC, SEN, SPE, PPV, NPV, AUC, and Dices were 0.88 (0.83~0.93), 0.85 (0.81~0.89), 0.90
| Study ID                      | Accuracy (95% CI)  | Weight (%) |
|------------------------------|--------------------|------------|
| Nico Buls                    | 0.93 (0.90, 0.96)  | 8.56       |
| Lu Li1                       | 0.94 (0.90, 0.99)  | 8.33       |
| Lu Li2                       | 0.49 (0.31, 0.67)  | 1.63       |
| Ruijuan Chen                 | 0.96 (0.94, 0.98)  | 8.69       |
| Suting Zhong                 | 0.98 (0.97, 1.00)  | 8.76       |
| Yu Lei1                      | 0.98 (0.97, 0.99)  | 8.78       |
| Yu Lei2                      | 0.91 (0.89, 0.92)  | 8.73       |
| Carlos Fernandez-Lozano      | 0.80 (0.75, 0.85)  | 7.86       |
| Andrew N. Hall               | 0.79 (0.77, 0.80)  | 8.71       |
| Jawed Nawabi                 | 0.77 (0.75, 0.78)  | 8.71       |
| Fengping Zhu                 | 0.98 (0.94, 0.99)  | 8.61       |
| Yiqing Zhao                  | 0.80 (0.68, 0.89)  | 5.82       |
| Yoshiyuki Watanabe           | 0.81 (0.73, 0.89)  | 6.79       |
| Overall (I^2 = 98.6%, P < 0.001) | 0.88 (0.83, 0.93)  | 100.00     |

NOTE: Weights are from random effects analysis

---

| Study ID                      | Sensitivity (95% CI)  | Weight (%) |
|------------------------------|-----------------------|------------|
| Ryan A. Rava                 | 0.93 (0.90, 0.96)     | 9.44       |
| Jeremy J. Heit               | 0.96 (0.91, 0.98)     | 9.36       |
| Nico Buls                    | 0.84 (0.68, 0.94)     | 4.76       |
| Danial Ginat                 | 0.88 (0.88, 0.90)     | 9.79       |
| Yu Lei1                      | 0.97 (0.93, 1.00)     | 9.35       |
| Yu Lei2                      | 0.94 (0.91, 0.97)     | 9.51       |
| Jawed Nawabi                 | 0.77 (0.75, 0.79)     | 9.57       |
| Stefan Pszczolkowski1        | 0.63 (0.55, 0.72)     | 5.89       |
| Stefan Pszczolkowski2        | 0.70 (0.64, 0.75)     | 7.79       |
| Linyang Teng                 | 0.82 (0.79, 0.84)     | 9.43       |
| Joel McLouth                 | 0.91 (0.87, 0.94)     | 9.23       |
| Yoshiyuki Watanabe           | 0.74 (0.64, 0.83)     | 5.88       |
| Overall (I^2 = 95.9%, P < 0.001) | 0.85 (0.81, 0.89)     | 100.00     |

NOTE: Weights are from random effects analysis

Figure 3: Continued.
**Table:**

| Study ID                  | Specificy (95% CI)  | Weight (%) |
|---------------------------|---------------------|------------|
| Ryan A. Rava              | 0.93 (0.92, 0.94)   | 10.24      |
| Jeremy J. Heit            | 0.95 (0.91, 0.98)   | 8.22       |
| Nico Buls                 | 0.94 (0.91, 0.96)   | 9.17       |
| Danial Ginat              | 0.96 (0.96, 0.97)   | 10.43      |
| Yu Leu1                   | 0.98 (0.97, 0.99)   | 10.27      |
| Yu Lei2                   | 0.90 (0.86, 0.94)   | 7.90       |
| Jawed Nawabi              | 0.76 (0.72, 0.79)   | 7.34       |
| Stefan Pszczolkowski1     | 0.69 (0.64, 0.74)   | 5.56       |
| Stefan Pszczolkowski2     | 0.74 (0.69, 0.80)   | 5.14       |
| Linyang Teng              | 0.71 (0.66, 0.76)   | 5.21       |
| Joel McLouth              | 0.98 (0.96, 0.99)   | 10.06      |
| Yoshiyuki Watanabe        | 0.99 (0.99, 0.99)   | 10.47      |
| Overall ($I^2 = 98.5\%, P < 0.001$) | 0.90 (0.88, 0.92) | 100.00    |

**NOTE:** Weights are from random effects analysis.

**Figure 3:** Continued.
| Study ID | Negative Predictive Value (95% CI) | Weight (%) |
|----------|----------------------------------|------------|
| Ryan A. Rava | 0.98 (0.97, 0.99) | 15.78 |
| Jeremy J. Heit | 0.95 (0.91, 0.98) | 11.40 |
| Nico Buls | 0.98 (0.96, 0.99) | 15.17 |
| Danial Ginat | 0.96 (0.96, 0.97) | 16.19 |
| Jawed Nawabi | 0.94 (0.93, 0.95) | 15.74 |
| Stefan Pszczolkowski1 | 0.84 (0.80, 0.88) | 9.47 |
| Stefan Pszczolkowski2 | 0.71 (0.66, 0.76) | 5.82 |
| Yiqing Zhao | 0.92 (0.90, 0.98) | 10.42 |
| Overall ($I^2 = 94.7\%, P < 0.001$) | 0.93 (0.91, 0.95) | 100.00 |

NOTE: Weights are from random effects analysis

| Study ID | Area Under Curve (95% CI) | Weight (%) |
|----------|---------------------------|------------|
| Chang Ho Kim | 0.97 (0.95, 0.98) | 7.72 |
| Suting Zhong | 0.85 (0.81, 0.88) | 7.40 |
| Carlos Fernandez-Lozano | 0.88 (0.83, 0.92) | 7.24 |
| Andrew N. Hall | 0.85 (0.84, 0.87) | 7.68 |
| Jawed Nawabi | 0.84 (0.83, 0.86) | 7.68 |
| Xinghua Xu | 0.92 (0.82, 0.97) | 6.50 |
| Masahito Katsuki | 0.88 (0.75, 1.00) | 5.02 |
| Fengping Zhu | 0.98 (0.96, 0.99) | 7.67 |
| Qian Chen | 0.82 (0.77, 0.88) | 6.92 |
| Stefan Pszczolkowski1 | 0.69 (0.64, 0.75) | 6.63 |
| Stefan Pszczolkowski2 | 0.78 (0.74, 0.82) | 7.25 |
| Zuhua Song | 0.87 (0.85, 0.95) | 7.19 |
| Linyang Teng | 0.78 (0.76, 0.80) | 7.63 |
| Masahito Katsuki | 0.73 (0.68, 0.73) | 7.47 |
| Overall ($I^2 = 98.1\%, P < 0.001$) | 0.84 (0.80, 0.89) | 100.00 |

NOTE: Weights are from random effects analysis

Figure 3: Continued.
NOTE: Weights are from random effects analysis

| Study ID         | Scores (95% CI) | Weight (%) |
|------------------|----------------|------------|
| Valeriia Abramova| 0.86 (0.79, 0.94) | 29.55      |
| Matthew F. Sharrock| 0.91 (0.87, 0.95) | 70.45      |
| Overall ($I^2 = 28.5\%, P = 0.237$) | 0.90 (0.85, 0.95) | 100.00     |

NOTE: Weights are from random effects analysis

Figure 3: Pooled accuracy/sensitivity/specificity/positive predictive value/negative predictive value/area under curve/dice scores of artificial intelligence used in ICH diagnosis.

(0.88–0.92), 0.80 (0.75–0.85), 0.93 (0.91–0.95), 0.84 (0.80–0.89), and 0.90 (0.85–0.95). Heterogeneity of pooled ACC, SEN, SPE, PPV, NPV, AUC, and Dices were 98.6% ($p < 0.001$), 95.9% ($p < 0.001$), 98.5% ($p < 0.001$), 95.1% ($p < 0.001$), 94.7% ($p < 0.001$), 98.1% ($p < 0.001$), and 28.5% ($p = 0.237$), respectively (Figure 3).

3.4. Publication Bias and Sensibility Analysis. There was symmetrical distribution in funnel plots (Figure 4). In sensibility analysis, after the study with the highest quality omitted or random effect model was transformed to the fixed effect model, pooled ACC (Fengping Zhu), SEN (Linyang Teng), SPE (Linyang Teng), PPV (Stefan Pszczołkowski), NPV (Stefan Pszczołkowski), AUC (Linyang Teng), and Dices (no article omitted because only 2 articles were included to perform meta-analysis of Dices) were 0.87 (0.82–0.92) or 0.92 (0.92–0.93), 0.85 (0.81–0.90) or 0.88 (0.87–0.89), 0.91 (0.89–0.93) or 0.99 (0.99–0.99), 0.88 (0.84–0.91) or 0.87 (0.86–0.88), 0.96 (0.95–0.97) or 0.96 (0.96–0.97), 0.85 (0.80–0.89) or 0.89 (0.89–0.90), and 0.90 (0.87–0.94). Heterogeneity of pooled ACC, SEN, SPE, PPV, NPV, AUC, and Dices in sensibility analysis was 98.7% ($p < 0.001$) or 98.6% ($p < 0.001$), 96.0% ($p < 0.001$) or 95.9% ($p < 0.001$), 98.5% ($p < 0.001$) or 98.5% ($p < 0.001$), 88.9% ($p < 0.001$) or 95.1% ($p < 0.001$), 87.8% ($p < 0.001$) or 94.7% ($p < 0.001$), 97.8% ($p < 0.001$) or 98.1% ($p < 0.001$), and 28.5% ($p = 0.235$) (Table 2).

3.5. Subgroups Analysis. Due to high heterogeneity companying, the study with the lowest quality might be the source of this phenomenon. After those studies omitted in the meta-analysis of ACC (Yoshiyuki Watanabe), SEN (Yoshiyuki Watanabe), SPE (Yoshiyuki Watanabe), PPV (Ryan A. Rava), NPV (Ryan A. Rava), and AUC (Zuhua Song), pooled effects were 0.88 (0.83–0.94), 0.86 (0.81–0.90), 0.88 (0.88–0.91), 0.78 (0.72–0.84), 0.92 (0.89–0.94), and 0.84 (0.79–0.89) with the heterogeneity of 98.7% ($p < 0.001$), 96.2% ($p < 0.001$), 97.4% ($p < 0.001$), 95.7% ($p < 0.001$), 94.8% ($p < 0.001$), and 98.2% ($p < 0.001$) (Table 2).

However, heterogeneity was still high. We considered that different aims of studies might be another source. Therefore, we performed subgroup analysis of ICH detection, ICH segmentation, ICH prediction, and hematoma enlargement (Figure 5). In subgroup analysis of ICH detection, pooled ACC, SEN, SPE, PPV, NPV, and AUC were 0.92 (0.89–0.95), 0.92 (0.88–0.95), 0.96 (0.94–0.98), 0.87 (0.82–0.92), 0.97 (0.95–0.98), and 0.84 (0.64–1.10). Their heterogeneity was 91.6% ($p < 0.001$), 88.2% ($p < 0.001$), 98.0% ($p < 0.001$), 90.3% ($p < 0.001$), 76.3% ($p = 0.001$), and 99.5% ($p < 0.001$). In the subgroup analysis of ICH segmentation, pooled ACC and AUC were 0.70 (0.37–1.33) and 0.90 (0.85–0.95). Their heterogeneity was 90.5% ($p < 0.001$) and 28.5% ($p = 0.237$). In the subgroup analysis of ICH prediction, pooled ACC, SEN, SPE, PPV, NPV, and AUC were 0.86 (0.76–0.97), 0.74 (0.67–0.81), 0.75 (0.73–0.78), 0.81 (0.66–0.98), 0.82 (0.62–1.08), and 0.87 (0.82–0.92). Their heterogeneity was 99.3% ($p < 0.001$), 80.7% ($p = 0.023$), 0.0% ($p = 0.563$), 95.9% ($p < 0.001$), 98.0% ($p = 0.001$), and 96.4% ($p < 0.001$). In the subgroup analysis of Hematoma Enlargement, pooled SEN, SPE, and AUC were 0.73 (0.53–0.93), 0.70 (0.67–0.73), and 0.79 (0.73–0.85). Their heterogeneity was 92.9% ($p < 0.001$), 0.0% ($p = 0.586$), and 87.8% ($p < 0.001$).

4. Discussion

We performed a novel systemic review and meta-analysis based on studies with high qualities in general. According to total meta-analysis of data, the diagnosis effect of AI was ACC > 0.83, Dices > 0.85, AUC > 0.80, SEN > 0.81, SPE > 0.88, PPV > 0.75, and NPV > 0.91 with a stable outcome of sensibility analysis, which might mean a relatively high agreement and similarity of full-manually
Figure 4: Continued.
Table 2: Sensitivity analysis of overall accuracy/sensitivity/specificity/positive predictive value/negative predictive value/area under curve/dice scores of artificial intelligence used in ICH diagnosis.

| Modification                  | Accuracy (95%CI) (Study) | Sensitivity (95%CI) (Study) | Specificity (95%CI) (Study) | Positive predictive value (95%CI) (Study) | Negative predictive value (95%CI) (Study) | Area under curve (95%CI) (Study) | Dice scores (95%CI) (Study) |
|-------------------------------|--------------------------|-----------------------------|----------------------------|------------------------------------------|------------------------------------------|---------------------------------|----------------------------|
| The study with the highest quality omitted | $I^2 = 98.7\%$ | $I^2 = 96.0\%$ | $I^2 = 98.5\%$ | $I^2 = 88.9\%$ | $I^2 = 87.8\%$ | $I^2 = 97.8\%$ | N/A |
| (Fengping Zhu)               | (0.82–0.92)              | (0.81–0.90)                 | (0.89–0.93)                | (0.84–0.91)                             | (0.96 (0.95–0.97)                       | (0.80–0.89)                      | N/A |
| The study with the lowest quality omitted | $I^2 = 98.7\%$ | $I^2 = 96.2\%$ | $I^2 = 97.4\%$ | $I^2 = 95.7\%$ | $I^2 = 94.8\%$ | $I^2 = 98.2\%$ | (0.84 |
| (Yoshiyuki Watanabe)         | (0.83–0.94)              | (0.81–0.90)                 | (0.88–0.91)                | (0.72–0.84)                             | (0.89–0.94)                             | (0.79–0.89)                      | N/A |
| Fixed effect model           | 0.92 (0.92–0.93)          | 0.86 (0.87–0.89)            | 0.99 (0.99–0.99)           | 0.97 (0.96–0.97)                         | 0.97 (0.96–0.97)                       | 0.89 (0.89–0.90)                 | 0.90 |

diagnostic conclusions, a relatively high authenticity of actual diagnostic conclusions, a relatively low rate of missed diagnosis and misdiagnosis, a relatively high accuracy of screening true ICH patients in people with risk of ICH, and a high accuracy of confirming true no risks of ICH in healthy people. Yet in the subgroup analysis of different aims, in addition to the great mass of outcomes in accord with total pooled effects, there were some invalid outcomes. The AUC of ICH detection was in the range of 0.64 to 1.10, which meant that it might be lack of authenticity for AI to detect ICH. The ACC of ICH segmentation was in the range of 0.37 to 1.33, which meant that the agreement of full-manually diagnostic conclusions might be controversial. For two abovementioned purposes, we considered that the factor-influenced identification of hematoma lesion via AI might be due to the fuzzy boundary between edema and hematoma during absorbing of ICH or in neuroimaging of small hematoma lesion. The NPV of ICH prediction was in the range of 0.62 to 1.08, which meant that AI might not confirm true ICH patients without some outcomes of prognosis. In this solution, we considered that subjectivity, which was unique to humans, might be the mingled influencing factor, because operation of AI was based on the binary system or other algorithmic languages, which was absolutely objective. Classification was usually involved in the assessment of prognosis in clinical work. Hence, when dealing with the common boundary of two grades, AI might not make decisions like humans flexibly, which might be a congenital defect of AI.

Limits also appeared in our meta-analysis. We only selected articles published in 2021, which might influence the results because we considered that recent AI technologies might remedy previous defects, which would reduce...
Table 5: Continued.

| Study ID          | ICH Detection (95% CI) | Weight (%) |
|-------------------|------------------------|------------|
| Accuracy          |                        |            |
| Nico Buls         | 0.93 (0.90, 0.96)      | 3.08       |
| Lu Li1            | 0.94 (0.90, 0.99)      | 2.68       |
| Lu Li2            | 0.49 (0.31, 0.67)      | 0.12       |
| Ruijuan Chen      | 0.96 (0.94, 0.98)      | 3.40       |
| YU Lei1           | 0.98 (0.97, 0.99)      | 3.62       |
| YU Lei2           | 0.91 (0.89, 0.92)      | 3.49       |
| Yiqing Zhao       | 0.80 (0.68, 0.89)      | 0.83       |
| Yoshiyuki Watanabe| 0.81 (0.73, 0.90)      | 1.24       |
| Subtotal (I² = 91.6%, p < 0.001) | 0.92 (0.89, 0.95) | 18.46     |
| Sensitivity       |                        |            |
| Ryan A. Rava      | 0.93 (0.90, 0.96)      | 3.08       |
| Jeremy J. Heit    | 0.96 (0.91, 0.98)      | 2.98       |
| Nico Buls         | 0.84 (0.68, 0.94)      | 0.62       |
| Daniel Ginat      | 0.88 (0.88, 0.90)      | 3.61       |
| Yu Lei1           | 0.97 (0.93, 1.00)      | 2.98       |
| Yu Lei2           | 0.94 (0.91, 0.97)      | 3.18       |
| Joel McLouth      | 0.91 (0.87, 0.94)      | 2.83       |
| Yoshiyuki Watanabe| 0.74 (0.64, 0.83)      | 0.89       |
| Subtotal (I² = 88.2%, p < 0.001) | 0.92 (0.88, 0.95) | 20.17     |
| Specificity       |                        |            |
| Ryan A. Rava      | 0.93 (0.92, 0.94)      | 3.61       |
| Jeremy J. Heit    | 0.95 (0.91, 0.98)      | 2.93       |
| Nico Buls         | 0.94 (0.91, 0.96)      | 3.25       |
| Daniel Ginat      | 0.96 (0.96, 0.97)      | 3.68       |
| Yu Lei1           | 0.98 (0.97, 0.99)      | 3.62       |
| Yu Lei2           | 0.90 (0.86, 0.94)      | 2.82       |
| Joel McLouth      | 0.98 (0.96, 0.99)      | 3.55       |
| Yoshiyuki Watanabe| 0.99 (0.99, 0.99)      | 3.69       |
| Subtotal (I² = 98.0%, p < 0.001) | 0.96 (0.94, 0.98) | 27.14     |
| Positive Predictive Value |            |            |
| Ryan A. Rava      | 0.85 (0.83, 0.87)      | 3.34       |
| Jeremy J. Heit    | 0.96 (0.91, 0.98)      | 2.98       |
| Nico Buls         | 0.61 (0.46, 0.74)      | 0.32       |
| Daniel Ginat      | 0.86 (0.84, 0.87)      | 3.49       |
| Yiqing Zhao       | 0.86 (0.74, 0.93)      | 1.06       |
| Subtotal (I² = 90.3%, p < 0.001) | 0.87 (0.82, 0.92) | 11.19     |
| Negative Predictive Value |            |            |
| Ryan A. Rava      | 0.98 (0.97, 0.99)      | 3.62       |
| Jeremy J. Heit    | 0.95 (0.91, 0.98)      | 2.93       |
| Nico Buls         | 0.98 (0.96, 0.99)      | 3.53       |
| Daniel Ginat      | 0.96 (0.96, 0.97)      | 3.68       |
| Yiqing Zhao       | 0.92 (0.90, 0.98)      | 2.75       |
| Subtotal (I² = 78.3%, p = 0.001) | 0.97 (0.95, 0.98) | 16.50     |
| Area Under Curve  |                        |            |
| Chang Ho Kim      | 0.97 (0.95, 0.98)      | 3.60       |
| Masahito Katsuki  | 0.73 (0.68, 0.73)      | 2.94       |
| Subtotal (I² = 99.5%, p < 0.001) | 0.84 (0.64, 1.10) | 6.54      |
| Overall (I² = 98.1%, p < 0.001) |            |            |

NOTE: Weights are from random effects analysis
| Study ID       | ICH Segmentation (95% CI) | Weight (%) |
|---------------|--------------------------|------------|
| Accuracy      |                          |            |
| Lu Li1        | 0.94 (0.90, 0.99)        | 34.98      |
| Lu Li2        | 0.49 (0.31, 0.67)        | 3.50       |
| Subtotal (I² = 90.5%, p = 0.001) | 0.70 (0.37, 1.33) | 38.47 |
| Dice          |                          |            |
| Valeriia Abramova | 0.86 (0.79, 0.94)      | 26.57      |
| Matthew F. Sharrock | 0.91 (0.87, 0.95)    | 34.96      |
| Subtotal (I² = 28.5%, p = 0.237) | 0.90 (0.85, 0.95) | 61.53 |
| Overall (I² = 77.4%, p = 0.004) | 0.89 (0.82, 0.96) | 100.00 |

NOTE: Weights are from random effects analysis

(b)

Figure 5: Continued.
| Study ID | ICH Prediction (95% CI) | Weight (%) |
|----------|-------------------------|------------|
| Accuracy |                         |            |
| Suting Zhong | 0.98 (0.97, 1.00) | 5.11 |
| Carlos Fernandez-Lozano | 0.80 (0.75, 0.85) | 4.59 |
| Andrew N. Hall | 0.79 (0.77, 0.80) | 5.08 |
| Jawed Nawabi | 0.77 (0.75, 0.78) | 5.08 |
| Fengping Zhu | 0.98 (0.94, 0.99) | 5.03 |
| Subtotal (I² = 99.3%, p < 0.001) | 0.86 (0.76, 0.97) | 24.90 |
| Sensitivity |                         |            |
| Jawed Nawabi | 0.77 (0.75, 0.79) | 5.04 |
| Stefan Pszczolkowski | 0.70 (0.64, 0.75) | 4.35 |
| Subtotal (I² = 80.7%, p = 0.023) | 0.74 (0.67, 0.81) | 9.39 |
| Specificity |                         |            |
| Jawed Nawabi | 0.76 (0.72, 0.79) | 4.85 |
| Stefan Pszczolkowski | 0.74 (0.69, 0.80) | 4.48 |
| Subtotal (I² = 0.0%, p = 0.563) | 0.75 (0.73, 0.78) | 9.33 |
| Positive Predictive Value |                         |            |
| Jawed Nawabi | 0.89 (0.87, 0.91) | 5.07 |
| Stefan Pszczolkowski | 0.73 (0.67, 0.78) | 4.42 |
| Subtotal (I² = 95.9%, p < 0.001) | 0.81 (0.66, 0.98) | 9.48 |
| Negative Predictive Value |                         |            |
| Jawed Nawabi | 0.94 (0.93, 0.95) | 5.12 |
| Stefan Pszczolkowski | 0.71 (0.66, 0.76) | 4.42 |
| Subtotal (I² = 98.0%, p < 0.001) | 0.82 (0.62, 1.08) | 9.54 |
| Area Under Curve |                         |            |
| Suting Zhong | 0.85 (0.81, 0.88) | 4.90 |
| Carlos Fernandez-Lozano | 0.88 (0.83, 0.92) | 4.80 |
| Andrew N. Hall | 0.85 (0.84, 0.87) | 5.10 |
| Jawed Nawabi | 0.84 (0.83, 0.86) | 5.09 |
| Xinghua Xu | 0.92 (0.82, 0.97) | 4.29 |
| Masahito Katsuki | 0.88 (0.75, 1.00) | 3.28 |
| Fengping Zhu | 0.98 (0.96, 0.99) | 5.09 |
| Stefan Pszczolkowski | 0.78 (0.74, 0.82) | 4.80 |
| Subtotal (I² = 96.4%, p < 0.001) | 0.87 (0.82, 0.92) | 37.35 |
| Overall (I² = 98.3%, p < 0.001) | 0.83 (0.80, 0.87) | 100.00 |

NOTE: Weights are from random effects analysis

Figure 5: Continued.
Significant heterogeneity was not in our study like the published meta-analysis of AI used in prevalence and diagnosis of neurological disorders [35], the causes of which might be as follows: (1) the AI models used in these included studies were different. The operation mechanisms or databases of the AI models differed across studies. (2) The research objectives also differed including the detection of ICH, segmentation of ICH in neuroimaging, prediction of prognosis, and hematoma enlargement in ICH patients. (3) ICH patients participated in few studies included not only intraparenchymal hemorrhage but also intraventricular hemorrhage, subdural hemorrhage, or subarachnoid hemorrhage. (4) All the original data used to assess diagnosis effect could be influenced to each other. (5) Number of samples was stark contrast.

In our opinion, although AI as a medical tool will bring great commercial profits to its designers and make the clinical work of doctors more efficient, whether AI systems can be used to diagnose ICH still requires more research evidences with cross-regional, multicenter, and large sample size. The objective and accurate division of hematoma, perihematoma edema, infarction focus, and normal tissue, especially in the stage of hematoma absorption and perihematoma edema developing, is the key for AI to analyze neuroimaging data of ICH. Moreover, when designers and researchers are constructing the database for mechanical learning, some potential problems may appear that the etiology classification of ICH is ambiguous, and the choice of research indicators or dependent variables is not comprehensive enough. Addressing these defects is closely related to continuously optimizing the clinical guideline of ICH. Therefore, while AI is updating, more evidences originated from high-quality and authoritative clinical researches are the real basis of its development of clinical applications.

5. Conclusion
Under the background of the fourth industrial revolution, AI might be an effective and efficient tool to assist doctors in the clinical diagnosis of ICH.

Data Availability
All data analyzed during this study are included in this published article.

Consent
Not applicable.

Disclosure
Kai Zhao and Qing Zhao are co-first authors.
Confl icts of Interest
The authors declare that they have no conflicts of interest.

Authors’ Contributions
Mingfei Yang and Kai Zhao conceived the idea and designed the study. Qing Zhao and Ping Zhou screened studies and extracted the data independently. Bin Liu and Qiang Zhang analyzed and interpreted the data. Kai Zhao and Qing Zhao wrote the first draft of the manuscript. Mingfei Yang proofread the manuscript before submission. All authors reviewed the manuscript and approved the final version.

Acknowledgments
This systemic review and meta-analysis was performed referring to the protocol published on the database of International Platform of Registered Systematic Review and Meta-analysis Protocols (INPLASY, https://inplasy.com/, registration number: INPLASY202180056, DOI number: 10.37766/inplasy2021.8.0056). This work was funded by the registration number: INPLASY202180056, DOI number:

Supplementary Materials
The PRISMA_2020_checklist of this study. (Supplementary Materials)

References
[1] T. Mahmood and M. S. Mubarik, "Balancing innovation and exploitation in the fourth industrial revolution: role of intellectual capital and technology absorptive capacity," Technological Forecasting and Social Change, vol. 160, pp. 120248–120257, 2020.

[2] D. Mhlanga, "Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: lessons from emerging economies?" Sustainability, vol. 13, no. 11, pp. 5788–5803, 2021.

[3] E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," Nature Medicine, vol. 25, no. 1, pp. 44–56, 2019.

[4] B. C. V. Campbell and P. Khatri, "Stroke," The Lancet, vol. 396, no. 10244, pp. 129–142, 2020.

[5] C. Tschoe, C. D. Bushnell, P. W. Duncan, M. A. Alexander-Miller, and S. Q. Wolfe, "Neuroinflammation after intracerebral hemorrhage and potential therapeutic targets," Journal of Stroke, vol. 22, no. 1, pp. 29–46, 2020.

[6] M. Katsuki, Y. Kakizawa, A. Nishikawa, Y. Yamamoto, and T. Uchiyama, "Endoscopic hematoma removal of supratentorial intracerebral hemorrhage under local anesthesia reduces operative time compared to craniotomy," Scientific Reports, vol. 10, no. 1, Article ID 10389, 2020.

[7] C. S. Kase and D. F. Hanley, "Intracerebral hemorrhage," Neurologic Clinics, vol. 39, no. 2, pp. 405–418, 2021.

[8] J. E. Soun, D. S. Chow, M. Nagamine et al., "Artificial intelligence and acute stroke imaging," American Journal of Neuroradiology, vol. 42, no. 1, pp. 2–11, 2021.

[9] V. Abramova, A. Clérigues, A. Quiles et al., "Hemorrhagic stroke lesion segmentation using a 3D U-net with squeeze-and-excitation blocks," Computerized Medical Imaging and Graphics, vol. 90, Article ID 101908, 2021.

[10] N. Buls, N. Wätte, K. Nieboer, B. Ilsen, and J. de Mey, "Performance of an artificial intelligence tool with real-time clinical workflow integration—detection of intracranial hemorrhage and pulmonary embolism," Physica Medica, vol. 83, pp. 154–160, 2021.

[11] L. Li, M. Wei, B. Liu et al., "Deep learning for hemorrhagic lesion detection and segmentation on brain CT images," IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 5, pp. 1646–1659, 2021.

[12] M. F. Sharrock, W. A. Mould, H. Ali et al., "3D deep neural network segmentation of intracerebral hemorrhage: development and validation for clinical trials," Neuroinformatics, vol. 19, no. 3, pp. 403–415, 2021.

[13] R. Chen, J. Huang, Y. Song, B. Li, J. Wang, and H. Wang, "Deep learning algorithms for brain disease detection with magnetic induction tomography," Medical Physics, vol. 48, no. 2, pp. 745–759, 2021.

[14] D. Ginat, "Implementation of machine learning software on the radiology worklist decreases scan view delay for the detection of intracranial hemorrhage on CT," Brain Sciences, vol. 11, no. 7, p. 832, 2021.

[15] S. Zhong, K. Sun, X. Zuo, and A. Chen, "Monitoring and prognostic analysis of severe cerebrovascular diseases based on multi-scale dynamic brain imaging," Frontiers in Neuroscience, vol. 15, Article ID 684469, 2021.

[16] Y. Lei, X. Zhang, W. Ni et al., "Recognition of moyamoya disease and its hemorrhagic risk using deep learning algorithms: sourced from retrospective studies," Neural Regeneration Research, vol. 16, no. 5, pp. 830–835, 2021.

[17] C. Fernandez-Lozano, P. Hervella, V. Mato-Abad et al., "Random forest-based prediction of stroke outcome," Scientific Reports, vol. 11, no. 1, Article ID 10071, 2021.

[18] A. N. Hall, B. Weaver, E. Liotta et al., "Identifying modifiable predictors of patient outcomes after intracerebral hemorrhage with machine learning," Neurocritical Care, vol. 34, no. 1, pp. 73–84, 2021.

[19] J. Nawabi, H. Kniep, S. Elsayed et al., "Imaging-based outcome prediction of acute intracerebral hemorrhage," Translational Stroke Research, vol. 12, no. 6, pp. 958–967, 2021.

[20] X. Xu, J. Zhang, K. Yang, Q. Wang, X. Chen, and B. Xu, "Prognostic prediction of hypertensive intracerebral hemorrhage using CT radiomics and machine learning," Brain and Behavior, vol. 11, no. 5, Article ID e02085, 2021.

[21] M. Katsuki, Y. Kakizawa, A. Nishikawa, Y. Yamamoto, and T. Uchiyama, "Post-surgical functional outcome prediction model using deep learning framework (prediction one, sony network communications inc.) for hypertensive intracerebral hemorrhage," Surgical Neurology International, vol. 12, p. 203, 2021.

[22] F. Zhu, Z. Pan, Y. Tang et al., "Machine learning models predict coagulopathy in spontaneous intracerebral hemorrhage patients in ER," CNS Neuroscience and Therapeutics, vol. 27, no. 1, pp. 92–100, 2021.

[23] Q. Chen, D. Zhu, J. Liu et al., "Clinical-radiomics nomogram for risk estimation of early hematoma expansion after acute intracerebral hemorrhage," Academic Radiology, vol. 28, no. 3, pp. 307–317, 2021.

[24] P. Pszczolkowski, J. P. Manzano-Patrón, Z. K. Law et al., "Quantitative CT radiomics-based models for prediction of haematoma expansion and poor functional outcome in
primary intracerebral haemorrhage,” *European Radiology*, vol. 31, no. 10, 2021.

[25] Z. Song, D. Guo, Z. Tang et al., “Noncontrast computed tomography-based radiomics analysis in discriminating early hematoma expansion after spontaneous intracerebral hemorrhage,” *Korean Journal of Radiology*, vol. 22, no. 3, pp. 415–424, 2021.

[26] L. Teng, Q. Ren, P. Zhang, Z. Wu, W. Guo, and T. Ren, “Artificial intelligence can effectively predict early hematoma expansion of intracerebral hemorrhage analyzing noncontrast computed tomography image,” *Frontiers in Aging Neuroscience*, vol. 13, Article ID 632138, 2021.

[27] M. Katsuki, N. Narita, N. Ishida et al., “Preliminary development of a prediction model for daily stroke occurrences based on meteorological and calendar information using deep learning framework (prediction one; sony network communications inc., Japan),” *Surgical Neurology International*, vol. 12, p. 31, 2021.

[28] Y. Zhao, S. Fu, S. J. Bielinski et al., “Natural language processing and machine learning for identifying incident stroke from electronic health records: algorithm development and validation,” *Journal of Medical Internet Research*, vol. 23, no. 3, Article ID e22951, 2021.

[29] J. McLouth, S. Elstrott, Y. Chaibi et al., “Validation of a deep learning tool in the detection of intracranial hemorrhage and large vessel occlusion,” *Frontiers in Neurology*, vol. 12, Article ID 656112, 2021.

[30] Y. Watanabe, T. Tanaka, A. Nishida et al., “Improvement of the diagnostic accuracy for intracranial haemorrhage using deep learning-based computer-assisted detection,” *Neuroradiology*, vol. 63, no. 5, pp. 713–720, 2021.

[31] R. A. Rava, S. E. Seymour, M. E. LaQue et al., “Assessment of an artificial intelligence algorithm for detection of intracranial hemorrhage,” *World Neurosurgery*, vol. 150, pp. e209–e217, 2021.

[32] C. H. Kim, M. H. Hahm, D. E. Lee et al., “Clinical usefulness of deep learning-based automated segmentation in intracranial hemorrhage,” *Technology and Health Care*, vol. 29, no. 5, pp. 881–895, 2021.

[33] J. J. Heit, H. Coelho, F. O. Lima et al., “Automated cerebral hemorrhage detection using RAPID,” *American Journal of Neuroradiology*, vol. 42, no. 2, pp. 273–278, 2021.

[34] S. J. Cho, L. Sunwoo, S. H. Baik, Y. J. Baek, B. S. Choi, and J. H. Kim, “Brain metastasis detection using machine learning: a systematic review and meta-analysis,” *Neuro-Oncology*, vol. 23, no. 2, pp. 214–225, 2021.

[35] R. Gautam and M. Sharma, “Prevalence and diagnosis of neurological disorders using different deep learning techniques: a meta-analysis,” *Journal of Medical Systems*, vol. 44, no. 2, p. 49, 2020.