# Supplementary Material

**Supplementary Table S1.** Summary of data used to construct Figure 3. The classification accuracy from the top performing algorithm on a distinct dataset within each research paper is included (n=67). If multiple distinct datasets were used in a single research paper, the top performing algorithm from each dataset was reported. Where papers did not include classification accuracy, data were not used, likely resulting in the underreporting of more recent research that are likely to provide F1-score, precision or recall values instead. Classification accuracy was selected given it is the metric most used in older research and allowed for a longer comparison period

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Feature Extraction** | **Classes** | **Accuracy (%)** | **Dataset Size** | **Year** | **Reference** |
| Manual | 8 | 69 | 50 | 1986 | (Guyer et al. 1986) |
| Manual | 6 | 82.3 | 300 | 1989 | (Petry and Kühbauch 1989) |
| Manual | 7 | 90 | 350 | 1990 | (Shearer and Holmes 1990) |
| Manual | 8 | 81.9 | 50 | 1993 | (Gerhards et al. 1993) |
| Manual | 10 | 74 | 100 | 1995 | (Woebbecke et al. 1995) |
| Manual | 3 | 54.9 | 54 | 2000 | (El-Faki et al. 2000) |
| Manual | 3 | 62.2 | 54 |  |
| Manual | 6 | 96.7 | 240 | 2000 | (Burks et al. 2000a) |
| Manual | 5 | 93 | 200 | 2000 | (Burks et al. 2000b) |
| Manual | 2 | 91 | 587 | 2002 | (Åstrand and Baerveldt 2002) |
| Manual | 6 | 96.7 | 240 | 2005 | (Burks et al. 2005) |
| Manual | 4 | 89.2 | 510 | 2006 | (Neto et al. 2006) |
| Manual | 3 | 75.4 | 18 | 2006 | (Gebhardt et al. 2006) |
| Manual | 3 | 70 | 18 |
| Manual | 3 | 69.7 | 18 |
| Manual | 20 | 91 | 400 | 2007 | (Du et al. 2007) |
| Manual | 3 | 82.7 | 18 | 2007 | (Gebhardt and Kühbauch 2007) |
| Manual | 3 | 80.4 | 18 |
| Manual | 3 | 75.9 | 18 |
| Manual | 20 | 92.6 | 1200 | 2008 | (Wang et al. 2008) |
| Manual | 10 | 90 | 150 | 2009 | (Backes and Bruno 2009) |
| Manual | 5 | 86.6 | 2325 | 2009 | (Lin 2009) |
| Manual | 3 | 75.9 | 107 |
| Manual | 2 | 100 | 18 | 2009 | (Wu and Wen 2009) |
| Manual | 32 | 79.7 | 2048 | 2010 | (Cope et al. 2010) |
| Manual | 3 | 86.4 | 286 | 2011 | (Golzarian and Frick 2011) |
| Manual | 2 | 97.5 | 139 | 2013 | (Giselsson et al. 2013) |
| Manual | 3 | 90.4 | 866 | 2014 | (Larese et al. 2014) |
| Manual | 3 | 95.1 | 3464 |
| Manual | 7 | 95.8 | 2438 | 2014 | (Dyrmann and Christiansen 2014) |
| Manual | 2 | 92.9 | 66 | 2014 | (Herrera et al. 2014) |
| Manual | 8 | 84.4 | 160 | 2015 | (Latte et al. 2015) |
| Manual | 2 | 99.1 | 474 | 2015 | (Kazmi et al. 2015a) |
| Manual | 2 | 97.8 | 474 | 2015 | (Kazmi et al. 2015b) |
| Convolutional | 22 | 86.2 | 10413 | 2016 | (Dyrmann et al. 2016) |
| Convolutional | 3 | 93 | 866 | 2016 | (Grinblat et al. 2016) |
| Convolutional | 3 | 96.9 | 3464 |
| Convolutional | 4 | 99.1 | 15336 | 2017 | (dos Santos Ferreira et al. 2017) |
| Convolutional | 44 | 99.5 | 43472 | 2017 | (Lee et al. 2017) |
| Convolutional | 44 | 97.7 | 2816 |
| Convolutional | 4 | 92.9 | 820 | 2017 | (Tang et al. 2017) |
| Manual | 2 | 92.1 | 30955 | 2017 | (Zheng et al. 2017) |
| Convolutional | 2 | 98.7 | 1100 | 2018 | (Suh et al. 2018) |
| Convolutional | 2 | 98.93 | 11786 | 2019 | (Kounalakis et al. 2019) |
| Convolutional | 8 | 95.7 | 17509 | 2019 | (Olsen et al. 2019) |
| Convolutional | 1 | 99 | 7282 | 2019 | (Yu et al. 2019) |
| Convolutional | 1 | 99 | 7282 |
| Convolutional | 1 | 99 | 3005 |
| Convolutional | 31 | 99.6 | 31147 | 2019 | (Zhang et al. 2019) |
| Manual | 8 | 92.3 | 1600 | 2019 |
| Manual | 2 | 95 | 396 | 2020 | (Alam et al. 2020) |
| Convolutional | 8 | 98.1 | 17509 | 2020 | (Hu et al. 2020) |
| Convolutional | 12 | 98 | 93130 | 2020 | (Peteinatos et al. 2020) |
| Convolutional | 4 | 97.6 | 17800 | 2020 | (Yu et al. 2020) |
| Convolutional | 4 | 96.51 | 7200 | 2020 | (Jiang et al. 2020) |
| Convolutional | 2 | 97.8 | 6000 |
| Convolutional | 2 | 99.37 | 800 |
| Convolutional | 2 | 98.93 | 400 |
| Convolutional | 4 | 98.9 | 462 | 2021 | (Ahmad et al. 2021) |
| Convolutional | 6 | 94 | 16500 | 2021 | (de Camargo et al. 2021) |
| Manual | 2 | 97.5 | 2400 | 2021 | (Chen et al. 2021) |
| Convolutional | 12 | 97.8 | 5544 | 2021 | (Farkhani et al. 2021) |
| Convolutional | 2 | 97 | 30160 | 2021 | (Hussain et al. 2021) |
| Manual | 2 | 96 | 1 | 2021 | (Islam et al. 2021) |
| Convolutional | 3 | 94.7 | 5400 | 2021 | (Khan et al. 2021) |
| Convolutional | 4 | 94 | 10180 | 2021 | (Zhang et al. 2021) |
| Convolutional | 2 | 97.7 | 1106 | 2022 | (Subeesh et al. 2022) |

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