**Appendix A**

For the sake of brevity, the critical analysis of the available literature needed to identify the research gap we aim to fill is reported in Table A1. Specifically, Table A1 reports the different papers available in the literature discussing the challenges of adopting ML for PdM, elaborating per each of them the sector they focus on and their main limitations. As it can be seen, no papers present empirical data, which is instead what we do with our work.

**Table A1**: Summary of the pertinent relevant documents. The table highlights the gaps that the related paper is trying to fill

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Paper title** | **Sector** | | **Approach** | | **Limitations** |
| **Industrial** | **Other** | **Literature** | **Empirical** |  |
| (Liskiewicz et al., 2023) | X |  | X |  | - Narrow focus on ML |
| (Chen et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Ogunfowora and Najjaran, 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Kamm et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Hurtado et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Surucu et al., 2023) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Govindarajan et al., 2023) | X |  | X |  | - Narrow focus on ML |
| (Singh et al., 2023) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Tran et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Rahal et al., 2023) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Ramírez et al., 2023) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Samie et al., 2024) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Hoffmann and Lasch, 2024) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Klaiber and Van Dinther, 2024) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Dalzochio et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Nguyen et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Wang et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Gawde et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Tama et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Ren et al., 2023) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Yazdani-Asrami et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Gonzalo et al., 2022) |  | Railway | X |  | - Not on industrial sectors or machines |
| (Zhu et al., 2021) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Wang and Yin, 2022) |  | Civil engineering |  |  | - Not on industrial sectors or machines |
| (Zhou et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Sanzana et al., 2022) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Suresh and Chakaravarthi, 2022) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Hallaji et al., 2022) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Ferreira and Gonçalves, 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Sholevar et al., 2022) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Rasol et al., 2022) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Esteban et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Butler et al., 2022) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Serradilla et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Fernandes et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Pan et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Wen et al., 2022) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Leukel et al., 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Maschler and Weyrich, 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Ahmed et al., 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Xia et al., 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Zhao et al., 2020) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Schwendemann et al., 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Ahmad et al., 2021) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Coutinho et al., 2021) |  | Civil engineering | X |  | - Not on industrial sectors or machines |
| (Theissler et al., 2021) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Kiranyaz et al., 2021) |  | General | X |  | - Narrow focus on predictive maintenance |
|  | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Erhan et al., 2021) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Baptista et al., 2021) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Dalzochio et al., 2020) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Gangsar and Tiwari, 2020) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Kumar et al., 2020) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Khan et al., 2020) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Zonta et al., 2020) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Hoffmann et al., 2020) | X |  | X |  | - Narrow focus on predictive maintenance |
| (Liang et al., 2019) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Rezaeianjouybari and Shang, 2020) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Fink et al., 2020) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Huckvale et al., 2019) |  | Medical | X |  | - Not on industrial sectors or machines |
| (Oromiehie et al., 2019) |  | General | X |  | - Narrow focus on predictive maintenance |
| (Carvalho et al., 2019) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Zhang et al., 2019) | X |  | X |  | - No empirical challenge  - No challenge prioritization  - No countermeasure prioritization |
| (Bousdekis et al., 2018) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Rafique and Velasco, 2018) |  | General | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Gerdes, 2013) | X |  | X |  | - No explicit challenge list/low focus on challenges related to ML for PdM |
| (Worden et al., 2011) | X |  | X |  | - Narrow focus on predictive maintenance |

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