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| **Author (year)** | **Objective of the study** | **Methodology/approaches/ tools/techniques used** | **Advantages** | **Disadvantages** |
| Iqra Mehmood; Sidra Shahid; Hameed Hussain; Inayat Khan; Shafiq Ahmad; Shahid Rahman  (2023) | - To improve Software Defect Prediction Accuracy | * Two-tail t-testing * SVM * Random Forrest * Logistic Regression * Baye’s Net * WEKA tool used | **Early Identification**: Predicts flaws in source code before testing, enabling early defect identification.  **Dataset-Centric Approach**: Recognizes the dependency on dataset characteristics for choosing appropriate prediction methods.  **Feature Selection**: Utilizes feature selection, improving the accuracy of specific algorithms like Bayesian Net. | **Future Work is Broad and Generic**:  Future work is somewhat generic;  specific goals or hypotheses could  enhance its focus.  **Complexity of Software Systems**  **Not Explored**: Although the study mentions the increasing complexity of software systems, it does not delve into how this complexity may impact the accuracy and effectiveness of defect prediction models. |
| Sushant Kumar Pandey, Ravi Bhushan Mishra, Anil Kumar Tripathi  (2021) | - Survey of Machine  learning based  methods for  Software Fault  Detection | * SVM * Logistic Regression * Baye’s Net * ANN * Decision Tree | * **Research Queries and**   **Protocols**: The formulation of research queries and the development of a review protocol based on previous articles demonstrate a methodical and evidence-based approach to gathering information.  **Score-Based Evaluation**: The use of scores in Tables A.14 to A.16, along with corresponding categories in Table A.9, provides a quantitative assessment of the relevance of articles to SFP over ML. This scoring system helps in prioritizing and understanding the significance of each study. | **Generalization of Results**: While  the study indicates an average  AUC range and accuracy for ML-  based SFP models, it does not  explicitly discuss the  generalizability of these results to  diverse datasets or project types.  **Dataset Availability**: The call for  freely available datasets by  industries is mentioned, indicating  a limitation in the availability of  datasets for SFP research. This can  constrain the scope of experiments. |
| Lei Qiao, Xuesong Li, Qasim Umer, Ping Guo  (2019) | -Deep Learning  Based Software  Defect Prediction. | * SVM * FSVR * DTR | **Versatility**: The proposed approach aims to predict the number of defects in software modules, showcasing its applicability across different projects and datasets.  **Change-Level Predictions**: The plan to investigate defect predictions at the change level . | **Overfitting Risk:** While the paper reports improved performance, there is a potential risk of overfitting to the specific datasets used. It's essential to ensure that the model generalizes well to new and unseen data, especially when applied to different projects and programming languages.  **Data Availability Hurdles:** The reliance on new and commercial datasets may encounter challenges due to access restriction. |
| **Author (year)** | **Objective of the study** | **Methodology/approaches/ tools/techniques used** | **Advantages** | **Disadvantages** |
| Thi Minh Phuong Ha, Duy Hung Tran, LE Thi My Hanh,  Nguyen Thanh Binh  (2019) | -To improve  Software Defect  Prediction Accuracy  (experimental study) | * Logistic Regression * SVM * Decision Tree * MLP * KNN * Naïve Bayes * Random Forrest | **Focused Use of Object-Oriented Metrics:** The study leverages object-oriented metrics, providing a specific and relevant set of indicators for evaluating and improving software quality.  **Performance Comparison:** Results highlight that Support Vector Machine excels in predicting faults at the class-level, while Multilayer Perceptron stands out for method-level datasets. This provides valuable insights for practitioners in selecting appropriate techniques for different aspects of software development.  **Practical Applicability:** By using real-world PROMISE datasets, the study ensures the practical relevance of its findings, enhancing the applicability of the results in real-world scenarios. | **Limited Exploration of**  **Classification Techniques:** The  mention of future work involving the  study of classification techniques to  address dataset imbalance implies that  this aspect has not been fully explored  in the current research. This could  limit the depth of understanding  regarding dataset challenges.  **Metrics and Techniques Selection:**  The study doesn't elaborate on the  rationale behind the choice of specific  object-oriented metrics or why these  seven machine learning techniques  were selected. Providing this context  could enhance the credibility and  transferability of the findings.  **Potential Biases in Results:** The  focus on only seven machine learning  techniques may introduce biases, and  the performance ranking could be  influenced by the chosen set. A  broader exploration of various  techniques might provide a more  nuanced understanding. |