1 Comparison

In this section, we undertake a critical comparison of closely related works addressing the challenges of imbalanced multiclass streams **??**, the emergence of new classes **??**, and the integration of transfer learning within streaming environments **??**. The increasing complexity of real-world data streams necessitates advanced methodologies that can effectively manage the intricacies of these challenges. By examining various approaches in the literature, we aim to highlight their contributions, strengths, and limitations in dealing with imbalanced data distributions, adapting to new class occurrences, and leveraging transfer learning techniques. This comparative analysis not only sheds light on the current state of research but also underscores the specific gaps and unresolved issues that our work seeks to address, ultimately paving the way for more robust and adaptive solutions in the realm of streaming data classification.

1.1 Imbalanced Stream

1.2 Emergence of New Classes

1.3 Transfer Learning

Method	Theory	Advantages	Limitations
MLSMOTE	MLSMOTE significantly enhances classifier performance by generating synthetic examples for each minority class label.	generating synthetic examples for each minority class label	• Random synthetic samples may be related to the majority class • Overlapping Classes
MLSOL	MLSOL systematically combats local imbalances within the domain of multi-class classification by employing distinct sampling strategies for each label	generating synthetic examples for each minority class label within a restricted neighborhood	• Overlapping Classes

Table 1: Comparison of MLSMOTE and MLSOL Methods