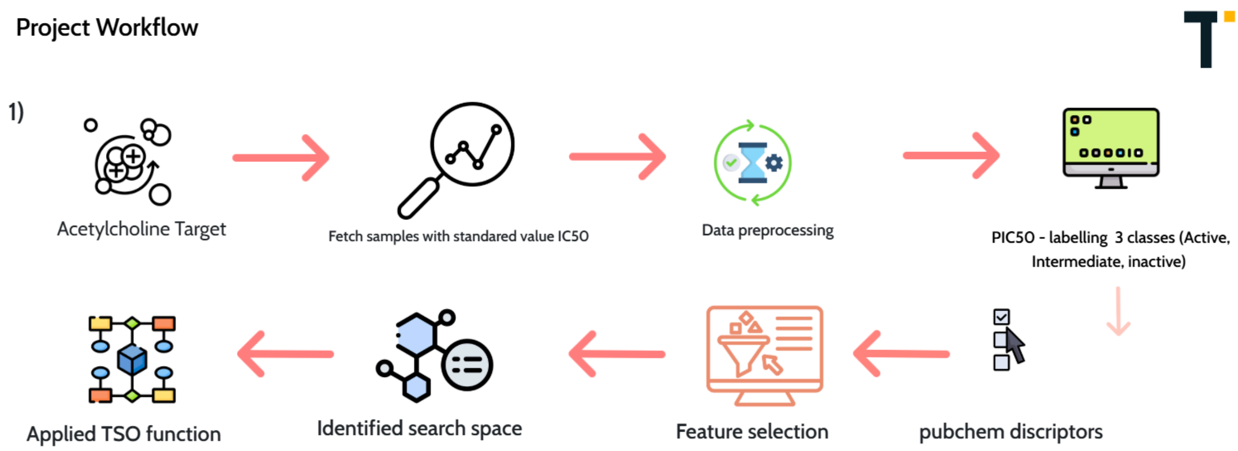
# Project Documentation

## 1. Project Architecture




1. **Data Preprocessing**:
   - Three datasets were created:
     - **Downsampled Data**: Reduced majority class to match minority class size.
     - **Unbalanced Data**: Original dataset used as it is.
     - **Oversampled Data**: Synthetic samples Oversampling Technique (SMOTE) was applied to balance the dataset.
   - Data splitting: 80% training and 20% testing.
2. **Model Building**:
   - Machine Learning Models:
     - Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbors (KNN), stacking, XGBoost (XGB).
   - Models were trained and evaluated on each dataset (downsampled, unbalanced, and oversampled).
3. **Optimization**:
   - **Tuna Swarm Optimization (TSO)** was used to fine-tune the hyperparameters for each model.
   - Fitness function: Cross-validation accuracy.
4. **Output**:
   - Best-performing models with optimized hyperparameters for each dataset.
   - Benchmarking for the models with the downsampling, unbalanced, and oversampling

## 2. Design Decisions

1. **Data Handling**:
    - **Imbalance Issue**: Addressed using downsampling and oversampling techniques to ensure fair performance evaluation.
    - Choice of SMOTE for oversampling was made due to its ability to create synthetic samples, enhancing generalization.
2. **Feature selection:**
    - Using recursive feature elimination with cross validation with random forest as an estimator
3. **Model Selection**:
    - Diverse models were chosen to test performance across complexity levels (e.g., simpler models like DT and KNN vs. advanced models like XGBoost and stacking).
4. **Optimization Algorithm**:
    - **TSO** was selected for hyperparameter optimization due to its proven efficiency in handling large search spaces compared to grid or random search.
5. **Evaluation Metrics**:
    - Chosen metrics were designed to evaluate performance on imbalanced datasets, prioritizing recall and F1-score for the minority class.

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## 3. Algorithms Used

1. **Tuna Swarm Optimization (TSO)**:
    - Inspired by the foraging and migration behavior of tuna fish.
    - The algorithm maintains a balance between exploration (searching new areas) and exploitation (refining existing solutions).
    - **Steps**:
        - Initialize a population of candidate solutions.
        - Evaluate fitness function for each candidate (cross-validation accuracy).
        - Update positions of candidates based on leader-following and random migration.
        - Iterate until convergence or a maximum number of iterations is reached.
2. **Synthetic Minority Oversampling Technique (SMOTE)**:
    - Generates synthetic examples for the minority class by interpolating between existing minority class samples and their nearest neighbors.
    - Reduces overfitting while addressing class imbalance.
3. **Machine Learning Models**:
    - **Random Forest (RF)**: Ensemble method using decision trees with bagging.

- **Support Vector Machine (SVM)**: Maximizes margin between classes using kernel functions.
- **Decision Tree (DT)**: Constructs a tree based on feature splits to classify data.
- **K-Nearest Neighbors (KNN)**: Classifies based on the majority label of k nearest data points.
- **Stacking:** Predict based on the integration of different base models for more accurate predictions.
- **XGBoost (XGB)**: Gradient boosting framework optimizing model accuracy.

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## 4. Dependencies

**Programming Language:**

- **Python 3.9**

**Libraries and Frameworks:**

- **Data Handling**:
    - pandas: For data manipulation.
    - numpy: For numerical operations.
- **Machine Learning**:
- scikit-learn:
    - StackingClassifier: For combining multiple base models using meta-models.
    - LogisticRegression: Used as a meta-classifier for stacked models or as a standalone model.
    - SVM: For implementing Support Vector Machine (SVM) models.
    - RandomForestClassifier, DecisionTreeClassifier, KNeighborsClassifier: For individual machine learning models.
    - SMOTE: For oversampling to address class imbalance.
    - train_test_split,
    - XGboost: For the XGBoost model.

- **Optimization**:

  Custom implementation of **Tuna Swarm Optimization (TSO)**.

**Environment:**

- Development environment: Jupyter Notebook or VS Code.
- Hardware: System with at least 8GB RAM and a multi-core processor for faster computations.