**Classification Report Insights**

* **Precision** is high across all three movement labels (1, 2, and 3), meaning the model makes very few false positive errors.
* **Recall** is 100% for classes 1 and 3, meaning it correctly identifies all instances of those classes.
* **Class 2 has slightly lower recall (86%)**, meaning the model **missed** some actual instances of class 2.
* The **F1-scores** are also strong (~0.95 on average), confirming a good balance between precision and recall.

**Confusion Matrix Insights**

* **Class 1 and Class 3 were perfectly classified (no false negatives)**.
* **Class 2 had 3 misclassifications**, where the model incorrectly labeled them as class 1.
* **No instances of misclassification between Class 1 and Class 3**, meaning these two classes are well separated in feature space.

**Possible Improvements**

1. **Improve Class 2 Recall**
   * Try **Hyperparameter Tuning** (adjusting tree depth, number of estimators, etc.).
   * **Feature Engineering**: Maybe class 2 lacks strong discriminative features.
   * **Try another classifier** (SVM, XGBoost) and compare results.
2. **Cross-Validation**
   * Run **k-fold cross-validation** to ensure the model generalizes well.
3. **Interpretability**
   * **SHAP or LIME analysis** could help explain why the model makes certain decisions.

**Result Interpretation**

* **Precision:** How many of the predicted labels were actually correct?
* **Recall:** How many of the actual labels were correctly predicted?
* **F1-Score:** The balance between precision and recall.

Each **Movement\_Label** corresponds to:

* **1 → T1 (Left Fist / Both Fists)**
* **2 → T2 (Right Fist / Both Feet)**
* **3 → T0 (Resting state)**

From your results:

* Class **1 (Left Fist/Both Fists)** has 88% precision and 100% recall → meaning all actual left fist movements were predicted correctly, but some false positives occurred.
* Class **2 (Right Fist/Both Feet)** has 100% precision but 86% recall → meaning some right fist movements were missed.
* Class **3 (Rest)** has perfect precision and recall (100%), meaning all rest states were classified correctly.

**2. How do we know which movement corresponds to which?**

Currently, the **Movement\_Label** column is being used to train the model. However, to **explicitly map these labels to real-world movements**, we should verify how these labels were assigned in the preprocessing stage.

Since the dataset has T1 and T2 mapped to different movements based on the runs (files), **we need to ensure that our labels correctly correspond to the expected motions**. For example:

* In **runs 3, 4, 7, 8, 11, 12**, **T1 is left fist**, and **T2 is right fist**.
* In **runs 5, 6, 9, 10, 13, 14**, **T1 is both fists**, and **T2 is both feet**.

If this mapping is not correct, we might be mislabeling classes.

**3. Can we deploy this to a simulator?**

Yes! A few ways to visualize and use this model in a practical setting:

* **Real-time EEG Movement Prediction:** We can use an **OpenBCI GUI** or a similar tool that takes live EEG data, applies preprocessing & feature extraction, and feeds it into our trained ML model to predict movement in real-time.
* **VR or Robot Control Simulation:** We can use Unity or Unreal Engine to link EEG movement predictions with animations, simulating hand movements in VR.
* **BCI Application:** If we integrate this into a **Brain-Computer Interface (BCI) pipeline**, we could control robotic arms or virtual cursors based on brain activity.

**4. What next steps should we take?**

**Verify movement labels:**

Ensure that T1 and T2 correctly correspond to left/right fists, both fists, and feet **for each run**. This is crucial to making meaningful conclusions.

**Test on new EEG data:**

* Can we test on different subjects or EEG datasets to see if the model generalizes?
* How does the model perform if we add noise (to simulate real-world brain signals)?

**Feature visualization:**

We can plot **CSP components** to see how brain activity differs across movements. If CSPs separate the movement classes well, we gain better interpretability.

**Deploy the model:**

Would you like to:

* Implement a **real-time EEG classifier**?
* Simulate EEG-controlled movement in a **VR or robotic system**?
* Deploy a **brain-controlled cursor or prosthetic hand**?

**1. Introduction**

**Background & Motivation**

* Brain-Computer Interfaces (BCI) enable direct communication between the brain and external devices.
* EEG (Electroencephalography) signals are widely used for motor imagery-based BCI applications.
* Our goal is to classify motor movements (left fist, right fist, both feet) based on EEG recordings.

**2. Project Objectives**

* Extract meaningful EEG features to classify motor movements.
* Apply machine learning techniques to predict movement intentions.
* Ensure high accuracy and model interpretability.
* Develop a framework that could be extended to real-world BCI applications.

**3. Dataset Overview**

**EEG Motor Movement/Imagery Dataset**

* Provided by PhysioNet and recorded using the **BCI2000** system.
* 109 subjects performed **14 experimental runs**, including real and imagined motor movements.
* Each subject completed:
  + **Resting-state EEG** (eyes open/closed)
  + **Motor movement tasks** (left/right fist, both fists/feet)
  + **Motor imagery tasks** (imagined movements)
* **64-channel EEG data**, recorded at **160 Hz**.
* **Annotations**:
  + **T0:** Rest
  + **T1:** Left fist / Both fists (based on session)
  + **T2:** Right fist / Both feet (based on session)

**4. Preprocessing & Data Cleaning**

**Steps Taken**

* **EDF File Handling:** Extracting raw EEG signals.
* **Merging Multiple Sessions:** Combining data across runs.
* **Filtering:** Applied **bandpass filter (1-40 Hz)** to remove noise.
* **Event Annotation Processing:** Mapping event labels (T0, T1, T2) to movement classes.
* **Missing Value Handling:** Identified and handled missing values in extracted features.

**5. Feature Engineering**

Extracted three types of features:

**Time-Domain Features**

* **Mean**, **Variance**, **Root Mean Square (RMS)**
* **Hjorth Parameters** (Activity, Mobility, Complexity)

**Frequency-Domain Features**

* **Power Spectral Density (PSD)**
* **Fourier Transform (FFT Mean)**

**Spatial Features**

* **Common Spatial Patterns (CSP)** – Helps distinguish movement-related EEG patterns.

**6. Balancing & Splitting the Data**

**Class Imbalance Handling**

* Initial dataset was highly imbalanced (more instances of one movement type).
* Applied **SMOTE (Synthetic Minority Oversampling Technique)** to create balanced classes.

**Data Splitting**

* **80% Training, 20% Testing**
* Ensured an even distribution of movement labels across both sets.

**7. Model Training & Results**

**Machine Learning Model Used**

* **Random Forest Classifier** (interpretable and robust for EEG data)
* Evaluated on:
  + **Accuracy** (95%)
  + **Precision, Recall, F1-score** (high across all classes)
  + **Confusion Matrix** (minimal misclassification)

**Feature Importance Analysis**

* **Top contributing features:** CSP components & Hjorth Mobility.
* **Spatial patterns (CSP) played the most significant role** in distinguishing movements.

**8. Interpretation & Next Steps**

**What The Results Mean**

* Our model can effectively **classify motor intentions** using EEG data.
* **CSP Features** were critical for classifying left/right fist and feet movements.
* High classification accuracy suggests potential **real-time application in BCI systems**.

**Future Work**

* **Deploy model on real-time BCI simulation**.
* **Test on additional subjects** to ensure robustness.
* **Optimize feature selection** to reduce dimensionality without accuracy loss.
* **Explore deep learning approaches** (CNNs on EEG signal matrices).

**Conclusion**

* Successfully classified EEG motor movements using **feature engineering & machine learning**.
* High accuracy achieved through **balanced data & CSP-based feature extraction**.
* Provides a foundation for **future real-time BCI implementations**.

**EEG Frequency Bands: Mu, Beta, and Gamma**

EEG signals are composed of different frequency bands, each associated with various brain functions. When analyzing motor movements using EEG, the Mu, Beta, and Gamma bands are particularly relevant.

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**1. Mu Band (8–12 Hz)**

**Function:** The Mu rhythm is closely associated with motor control and sensorimotor processing.

**Associated with:** Motor planning, execution, and imagery, particularly observed over the sensorimotor cortex.

**Important feature:** "Mu suppression" which occurs when a person performs a movement or observes another person moving.

**Location:** Most prominent in the sensorimotor cortex (around the central electrodes like C3, Cz, C4).

**Motor-Related Activity:**

**At rest:** Strong Mu activity is observed when no movement is occurring.

**During movement or motor imagery:** Mu activity suppresses (Mu desynchronization), meaning it decreases when the brain prepares for or executes movement.

**Importance in BCI:**

Mu suppression is a key feature for detecting real and imagined movements in Brain-Computer Interfaces.

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**2. Beta Band (13–30 Hz)**

**Function:** Associated with motor planning, execution, and post-movement feedback.

**Associated with:** Active thinking, focused attention, alertness, and motor execution

**Location:** Found in motor cortex regions, often overlapping with Mu activity.

**Motor-Related Activity:**

Beta desynchronization (decrease in power) occurs before and during movement.

Beta rebound (increase in power) happens after movement ends, likely related to motor inhibition.

**Importance in BCI:**

Beta band activity is useful for distinguishing different motor states (movement vs. rest).

Beta rhythms can provide real-time feedback in movement-based BCIs.

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**3. Gamma Band (30 Hz – Above)**

**Function:** Linked to motor learning, sensory processing, and cognitive functions.

**Associated with:** High-level cognitive functions like complex information processing, memory retrieval, and conscious perception

**Location:** Distributed across the sensorimotor cortex but more pronounced in higher-order cortical areas.

**Motor-Related Activity:**

Increases in gamma activity have been observed during movement initiation and execution.

May play a role in coordinating movement commands across different brain regions.

**Importance in BCI:**

Gamma band features are useful in distinguishing complex movements and mental states.

Some studies suggest that gamma synchronization is involved in high-level motor control.

**How These Bands Are Used in EEG-Based Motor Movement Prediction**

In our project, frequency-domain features like Power Spectral Density (PSD) and Fourier Transform (FFT Mean) help analyze these bands:

**Mu & Beta Bands:**

Movement-related desynchronization (decrease in power) in Mu and Beta is a strong indicator of motor intention.

Feature extraction in the 8-30 Hz range can improve classification accuracy.

**Gamma Band:**

Can be useful in advanced BCI applications but is often noisy due to muscle artifacts.

High-frequency activity (above 40 Hz) is sometimes filtered out to reduce noise.

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**Key Takeaways**

Mu (8-13 Hz) is suppressed during movement.

Beta (13-30 Hz) desynchronizes before movement and rebounds after.

Gamma (30-100 Hz) increases during movement but is prone to noise.

BCI systems rely heavily on Mu and Beta bands for motor decoding.