Transforming confidence scores both upward and downward can be beneficial for fine-tuning how the ensemble model interprets the base models' predictions, especially in situations where different base models have varying confidence distributions. Here's a breakdown of the advantages:

1. **Enhanced Sensitivity to High Confidence Scores**:
   - By **transforming scores upward** (e.g., using a non-linear function with an upward concave shape), the model places a stronger emphasis on high-confidence predictions.
   - This helps prioritize classes where base models have high agreement, making it less likely that the ensemble is swayed by lower-confidence or uncertain predictions.
   - This transformation aligns with the "rewarding" mechanism, where the ensemble output for a given class is more influenced when a base model has high confidence in that class.
2. **Mitigating Noise from Low Confidence Scores**:
   - **Downward transformations** (e.g., functions with downward concavity) can reduce the impact of low-confidence scores, which may represent noise or uncertainty in classification.
   - This allows the model to suppress classes that individual base models are less certain about, helping the ensemble focus on the most confident predictions across all models.
   - For instance, if a base model outputs low confidence in a class, this transformation prevents it from disproportionately affecting the final decision.
3. **Balancing High and Low Confidence Predictions**:
   - Combining both upward and downward transformations allows the model to balance between emphasizing high-confidence classes and downplaying low-confidence ones. This can lead to a more robust decision-making process in cases where:
     - Different base models vary significantly in their confidence distributions for a given class.
     - Base models perform inconsistently on certain classes due to factors like class imbalance or model specialization.
4. **Improving Model Calibration**:
   - Confidence transformations can indirectly improve calibration, making the ensemble's output probabilities better reflect the true likelihood of each class.

- For example, upward transformations can calibrate models that tend to underpredict, while downward transformations can calibrate models that tend to overpredict, resulting in more consistent and accurate final confidence scores.

5. **Better Handling of Ambiguity in Class Predictions**:
   - When a sample could reasonably belong to multiple classes, these transformations help the ensemble handle ambiguity by adjusting how confidence scores contribute to the final decision.
   - Upward transformations amplify the most likely classes, while downward transformations reduce the influence of highly uncertain classes, allowing the ensemble to focus on more definitive class distinctions.

6. **Improved Accuracy in Unconstrained Environments**:
   - In real-world applications with high variability, such as facial emotion recognition in unconstrained environments, these transformations provide a mechanism for the ensemble to adapt based on confidence level.
   - This can improve the ensemble's robustness by making it more responsive to high-confidence situations and less susceptible to uncertain or borderline cases, which are common in in-the-wild conditions.

By transforming the confidence scores both ways, you essentially enable the ensemble to leverage confidence more flexibly, which is crucial for scenarios where base models vary in certainty or where some predictions are more critical to get right than others.