

## **BAB 6**

### **KESIMPULAN DAN SARAN**

#### **6.1 Kesimpulan**

Berdasarkan hasil penelitian ini diperoleh beberapa kesimpulan sebagai berikut:

1. Dalam penelitian ini, model CNN berhasil diimplementasikan untuk tugas klasifikasi berbagai jenis kayu lokal berdasarkan citra kayu.
2. Setelah dilakukan pelatihan dan evaluasi terhadap model CNN, Xception dan MobileNetV2 menunjukkan tingkat akurasi yang tinggi, yaitu 94% untuk Xception dan 89% untuk MobileNetV2. Pada percobaan lanjutan, setelah dilakukan *fine-tuning*, akurasi Xception menjadi 99% dan 90% pada MobileNetV2. Analisis menunjukkan bahwa akurasi model dapat dipengaruhi oleh berbagai faktor, seperti pemilihan model, jumlah data pelatihan, jumlah *fine-tuning* dan jumlah epoch.

#### **6.2 Saran**

1. Perlunya penelitian yang model CNN lainnya untuk dilakukan perbandingan seperti ResNet, Inception dll.
2. Disarankan melatih model dengan menggunakan jumlah dataset yang lebih banyak dan jumlah kelas yang lebih banyak.

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