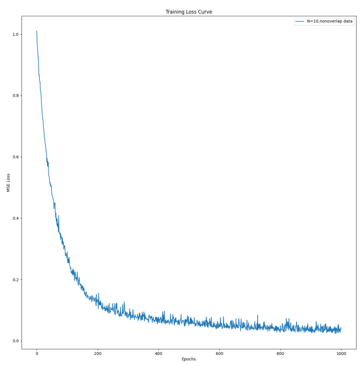
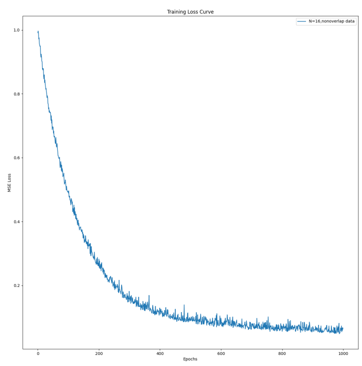
Parameter Name	Value	Parameter Name	Value
Batch Size	1 (nonoverlap) / 64 (overlap)	Epochs	1000
Learning Rate	0.0002	Diffusion Steps	1000
Diffusion Beta Start	0.0001	Diffusion Beta End	0.02
overlap status	True / False	N	[10, 16, 24, 32, 48, 60]
Residual Block (UNet)	4	Dropout	0.1

Table 1: Configuration data used for training

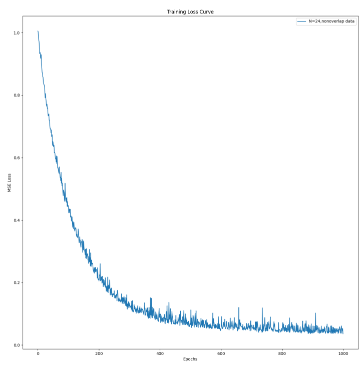
- Implemented an UNet model and trained using the diffusion paradigm using the configuration data (1).
- Loss curves (1) for models trained on non-overlap data converge at around MSE 0.1 for different N values, while loss curves (2) for models trained on overlap data converge at around MSE < 0.1 which conveys that overlapping data has better results. Reason being overlapping data has more training data points compared to it's counterpart.
- (3) combines the above loss curves into 1 plot, there is a clear separation between the models trained using overlap vs non-overlap data.
- GIFs in the results folder, we observe that for most of the cases in nonoverlap data, the model is not able to learn anything because of the few datapoints it has. But when N = 10 sometimes it's able to pickup the dance part because it has more datapoints to learn from.
- Similarly GIFs in the results for the overlap data, for low N values (10,16) it's able to generate the dance but it's unstable sometimes in the sense that the joints are not perfectly coordinated, while other N values it makes sure the motion is quite stable.



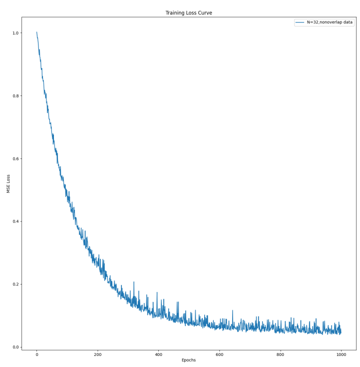
(a) N = 10



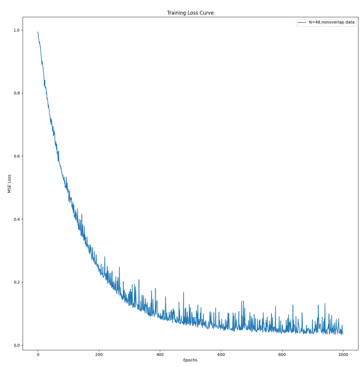
(b) N = 16



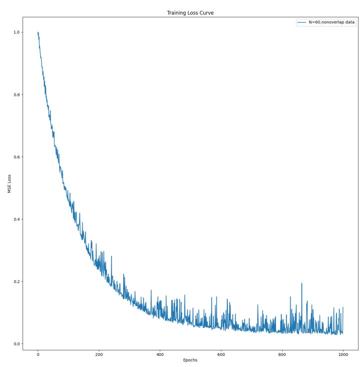
(c) N = 24



(d) N = 32

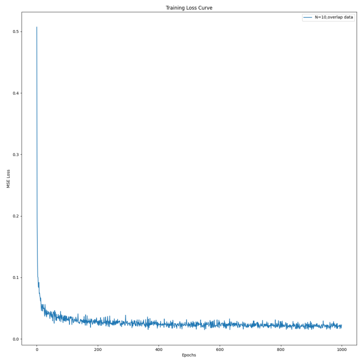


(e) N = 48

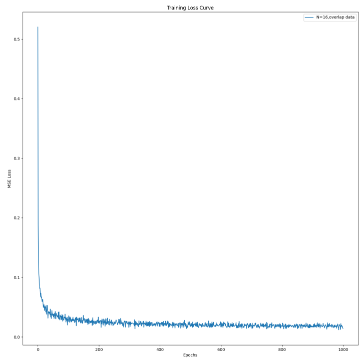


(f) N = 60

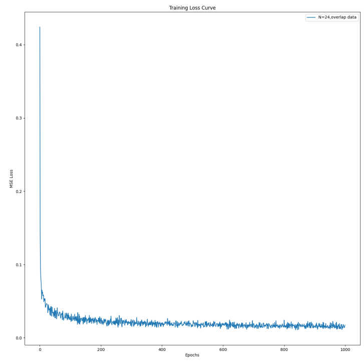
Figure 1: Loss Curves for different N values nonoverlapping data



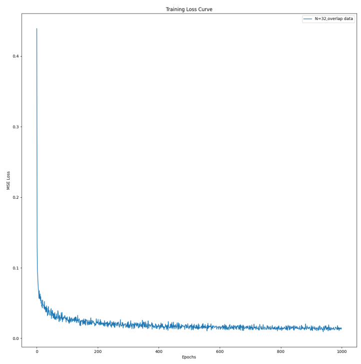
(a) N = 10



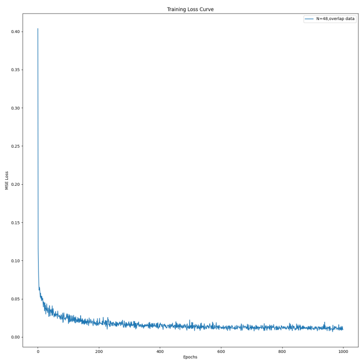
(b) N = 16



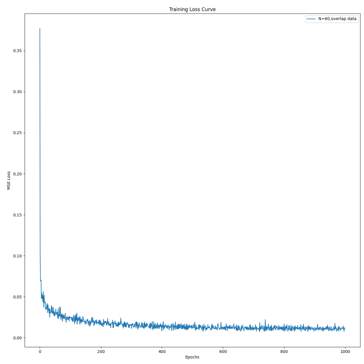
(c) N = 24



(d) N = 32



(e) N = 48



(f) N = 60

Figure 2: Loss Curves for different N values overlapping data

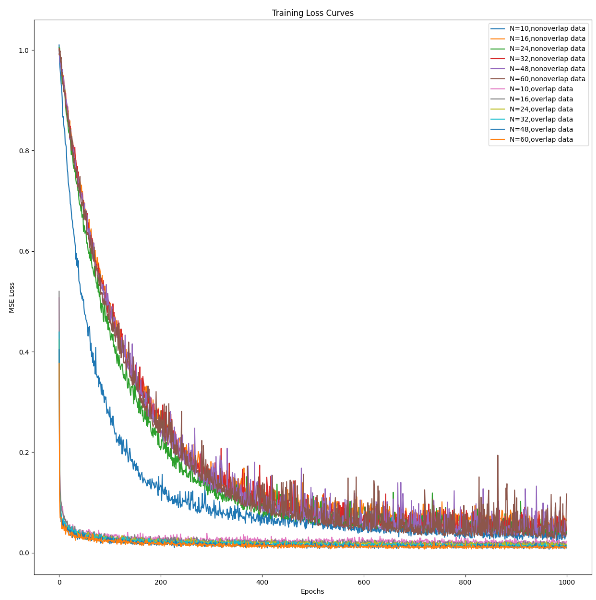


Figure 3: Loss Curves for different overlap and N values.