Let $m(X) = \mathbb{E}[Y|X]$ (regression function)

Then for any $f : \mathcal{X} \to \mathbb{R}$,

$$\mathbb{E}(f(X)-Y)^2 = \mathbb{E}\big((f(X)-m(X)) + (m(X)-Y)\big)^2$$

$$= \mathbb{E}(f(X)-m(X))^2 + \mathbb{E}(m(X)-Y)^2$$

$$+ 2\underbrace{\mathbb{E}\big[(f(X)-m(X))(m(X)-Y)\big]}$$

$$= \mathbb{E}\,\mathbb{E}\big[(f(X)-m(X))(m(X)-Y)\,|\,X\big]$$

$$= \mathbb{E}(f(X)-m(X))\underbrace{\mathbb{E}\big[m(X)-Y\,|\,X\big]}_{=0} = 0$$

$$= \underbrace{\mathbb{E}(f(X)-m(X))^2}_{\geq 0} - \mathbb{E}(m(X)-Y)^2$$

$$\geq \mathbb{E}(m(X)-Y)^2,$$

and therefore m is the optimal predictor under the squared loss.